REVERSE AUCTION BIDDING:

A STATISTICAL REVIEW OF THE FIRST CASE STUDY

A Thesis

by

DHAVAL CHANDRESH GUHYA

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

May 2010

Major Subject: Construction Management

Reverse Auction Bidding: A Statistical Review of the First Case Study

REVERSE AUCTION BIDDING:

A STATISTICAL REVIEW OF THE FIRST CASE STUDY

A Thesis

by

DHAVAL CHANDRESH GUHYA

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Approved by:

Co-Chairs of Committee,	John Nichols
	Leslie Feigenbaum
Committee Members,	George Rogers
Head of Department,	Joe Horlen

May 2010

Major Subject: Construction Management

ABSTRACT

Reverse Auction Bidding: A Review of the First Case Study.

(May 2010)

Dhaval Chandresh Guhya, B.E., University of Mumbai

Co-Chairs of Advisory Committee: Dr. John M Nichols
Dr. Leslie Feigenbaum

It was in 2004 that the first case study was done by on the ongoing Reverse Auction Bidding at Texas A&M University. This long-term study has developed from a single case study, completed by van Vleet, to a series of case studies, now combined with personality testing of all participants. van Vleet developed a Microsoft Access database system and Active Server Pages web based user interface for the study. The first case study involved five participants with no prior experience in Reverse Auction Bidding. A study with five participants is considered competitive in accordance with the standard economic Herfindahl Index. van Vleet, concluded that the results showed a level of co-operation in the bidding game between the nominal competitors. In 2010 John Nichols coined the term 'tacit collusion' to identify this apparent behavioural pattern observed in the bidding. A significant element of the studies from 2005 to 2009 has been to investigate the 'tacit collusion' behaviour. Tacit collusion is not considered an illegal economic behaviour. In 2006 Seth Gregory encountered significant problems with a study involving ten participants using the Access database, as a result of Access' limitations on the number of connections.

Gregory's study was migrated to a Microsoft SQL database that was developed by Wellington (2006) and which overcame the limitations. SQL database systems can generate a significant quantity of data which create a computer science problem, now commonly termed 'Data rich – analysis poor'. This study is the first in a series of studies to undertake a detailed statistical study of the early case studies to provide a set of algorithms for development of SQL queries for automated real-time data analysis of future Reverse Auction Bidding case studies.

This study showed that a fifth order polynomial fit the contract time compared to the job number. Analysis of the number of bids per minute for the fifteen minutes of bid time showed a log–polynomial equation which provided a reasonable fit to the data.

Two sub-games were postulated to describe the operational aspects of the auction. The first game, termed the α game, is between the players with the objective of maximizing average return and the second game, termed the ω game, has the objective of average cost minimization for the purchasers and maximization of revenue for the seller group.

In conclusion, Reverse Auction Bidding systems are not bid shopping, but the tenet that the purchaser will reduce costs in this type of system compared to the traditional closed bid system is not confirmed with van Vleet's data and any careful consideration of the results of canny players in the α game suggests higher than average returns for some bidders. The results show a number of patterns in the data that warrant further study, particularly the characteristics of the canny players.

DEDICATION

I want to thank all my friends at Texas A&M University who guided and encouraged me throughout my research especially Maddy, Suketu and Akshata.

Lastly, I would like to express my love and adoration for my family whose support has been invaluable throughout my life.

ACKNOWLEDGEMENTS

First of all, I would like to sincerely thank Dr. John Nichols for encouraging, helping and constantly supporting me throughout my master's program at Texas A&M University. "Without his guidance I would not have been able to complete my master's program and I thank god for providing me an opportunity to work with him during my masters who stood by me until I succeeded." I can honestly say that he is one of the best teachers I have had in my 20 years of education.

I also genuinely thank Dr. Leslie Feigenbaum and Dr. George Rogers for serving on my committee and guiding me throughout this research. They have reinforced my faith in the faculty at Texas A&M University.

TABLE OF CONTENTS

Page

LIST OF FIGURES

Page

Page

LIST OF TABLES

Page

CHAPTER I

INTRODUCTION

BACKGROUND OF THE STUDY

The OED (Little, Fowler, Coulson, Onions, & Friedrichsen, 1973) defines a bid as "*the offer of a price*". The traditional form of obtaining a bid is to request a price from one or more entities, such as a builder, contractor or company, with the bid due at a specific time and place. This system of bidding is considered by most to be free of collusive influences. Alternative forms of bidding have been developed over the centuries; some suffer from the need for a subjective judgment about the ability of the bidder to perform the work, although prequalification may overcome this problem.

One alternative purchase method is shopping, defined by the OED as "*The action of visiting a shop or shops for the purpose of inspecting or buying goods*." The difference between bidding and shopping is the visibility of the object, in shopping inspection is possible. Whilst in construction bidding, the item sought is usually unique and merely shown on a set of drawings. Shops traditionally display a price and operate in a free market, where market is defined by the OED as "*The meeting together of people for the purchase and sale of provisions or livestock, publically exposed, at a fixed time and place; the time of this; also the assembled company,*" with minimal outside intervention and providing transparency to the hagglers.

This thesis follows the style of *Adult Education Quarterly*.

To haggle is defined by the OED, for the purposes of this study, is '*to cavil, wrangle, dispute as to terms:, esp., to make difficulties in setting a bargain'*. Haggling is not illegal and it is common in some shopping situations or systems, Whereas collusion, defined by the OED as '*secret agreement or understanding for the purpose of trickery or fraud*', is generally considered to be reprehensible and is usually illegal in a free market system, because of the economic distortions introduced into the market.

Bid shopping is the practice of taking an offer prepared by a competent bidder and asking another distinct entity to match or beat the price. In a free market, each bidder is aware of the average expenditure required to gain a sale; as an example, in consulting engineering the amount of eight percent of the fee is generally considered reasonable for recovering the costs of preparing bids (Nichols, 2009) . In bid shopping, the second entity does not have to cover the cost of preparing multiple bids to obtain work, which is perceived as economically unfair and outs to distort the market.

Reverse Auction Bid Systems were developed for the internet to facilitate purchase of goods, where the concept of the 'traditional market' has broken down, often when the purchaser and seller cannot meet in the same place or it is difficult to meet in a common place. Reverse Auction Bidding systems are considered by some contractors as being an alternative form of bid shopping. Nichols (2009) considers Reverse Auction Bidding Systems, when operated by an independent entity of the purchaser, represents an electronic equivalent of a free market.

A Reverse Auction Bidding System can be viewed as multiplayer game, with two sub-games. The first sub-game, designated α game, is between the bidders and the second is the game between the bidding group and the purchaser, designated the ω game. The α game is a multi-player game; however the ω game reduces in reality to a two-player game, with only one effective player able to make moves. The reduction of the ω game to an equivalent two player game can be viewed as maximizing the return to the bidding group, designated λ player, at the expense of the purchaser, designated υ player. Several case studies have been completed for a simple Reverse Auction Bidding scenario developed by van Vleet (2004).

The purpose of this research work is to review the data collected by van Vleet, in the first case study, to establish analysis techniques and algorithms that can be incorporated into the SQL database as queries for future studies.

RESEARCH OBJECTIVE

A five person case study was completed in 2004 (van Vleet, 2004) using a Reverse Auction Bidding System that had recently been developed by Kim (2004). van Vleet (2004) analysed the data obtained from the first case study but lacked the information available after the completion of seven case studies in the period 2005 to 2009 to determine the critical elements from the data for this first case study in 2004.

The research objectives for this study are:

1. Establish plots of the bidding data
2. Compare the bidding patterns shown in the plots with time for all bidders
3. Determine if evidence exists in the bidding data to confirm the existence of the ω game and does it represent some form of collusion

4. Compare the returns of the different bidders in the α game to determine if there are differences in bidding returns and does it represent some form of collusion.

LIMITATIONS

The limitations of the study are:

1. the data obtained in van Vleet's initial case study and Chouhan's recent case study (Chouhan, 2009) will be used in the analysis, with Chouhan's data used for comparison purposes only
2. all bidders were students or academic faculty in the Department of Construction Science. In van Vleet's study none of the participants had prior experience with Reverse Auction Bidding and in Chouhan's study at least one of the participants had experience with an earlier case study
3. the prior experience of one bidder in the Chouhan's study, limits a direct comparison of the results
4. steady state economic conditions are assumed for the case study period.

SIGNIFICANCE OF THE STUDY

van Vleet noted in 2004 that "*In order to accurately assess the implications of reverse auctions, it was essential to know and understand the behaviours of those who engage in the bidding process. Without a method of evaluating the process, it is impossible to clearly understand whether RAB is a success or not. Therefore, by creating a simulation or model of an RAB, this research was able to collect and analyze substantial data which will contribute to the further understanding of the implications* *that RAB will have on the construction industry*" This study reviews the data from van Vleet's study to provide guidance in the development of tools to analyze subsequent case studies using the SQL database developed for Gregory's study in 2006.

CHAPTER II

LITERATURE REVIEW

INTRODUCTION

Reverse Auction Bidding has been studied in the Construction Science Department since 2004. This study looks at the original game or case study completed by van Vleet (2004), to determine methods for automating the SQL database analysis of results from subsequent and future case studies. This literature review outlines the definitions for the game, the game type and a brief review of Reverse Auction Bidding. Chouhan (2009) provides a more detailed review of the Reverse Auction Bidding system.

DEFINITIONS

This research is a continuation of previous Reverse Auction Bidding studies. Previous definitions established by van Vleet (2004), Gregory (2006), Chouhan (2009), Chaudary,(2009) and Panchal (2007) are included in this list.

The necessary definitions are:

λ player	This represents the bidder group, treated as a single entity for the purpose of game analysis.
λ_i player	The i^{th} bidder in the bidding group.
υ player	This represents the purchaser.

α game	The postulated sub-game played between bidders in seeking economic advantage over the remaining bidders. This game almost always disadvantages the υ player, but the υ player created the system and so is responsible for the υ player's economic losses as a result.
ω game	The postulated sub-game played within the Reverse Auction Bidding game between the purchaser and the bidders. In terms of this analysis, it is deemed to effectively reduce to a two-player game, with competition implications for all players. The υ player in reality sees only the average of all won bids.
τ	Bid time allowed for each round of play in the game.
δ	Period between bid time τ that represents the work time in the game.
B_j	ith bid
B_v	Accepted bid for each job.
K	This variable is a fixed dollar sum, representing the υ player's base price, although in this game K is a vector of costs.
Γ	This variable is a fixed dollar sum, representing the υ player's maximum incremental price above K

Ξ This variable is normally defined by the set of numbers $\{\Xi \mid 0 < \Xi \leq 1\}$, although negative values of Ξ are permitted by the Reverse Auction Bidding system. Ξ is used to normalize the profit data. A negative Ξ_j represents a loss on direct costs to the λ_i player who makes this type of bid, and enough of these bids will lead to a bankrupt player. This type of play is discouraged as the assumption in the game is steady state economic conditions in the outside economy. Future studies may look at a failing market, but that is beyond this study.

<u>Aggressive Bidder</u>: Willing to accept calculated risk of greater than average loss in pursuit of greater than average returns, first defined by Chouhan (2009).

<u>Bid:</u> A single entry into the game that represents a legally acceptable offer to complete the work assuming the bidder has been prequalified.

<u>Bidder:</u> An entity that submits a bid. In this game, there are usually three to ten bidders, and each is an individual, rather than a company. In van Vleet's (2004) study, none of the bidders had prior experience, which is not true for Chouhan's (Chouhan, 2009) study.

<u>Bid Efficiency</u>: The ratio of the total number of jobs won to the total number of bids. This is one of the postulated metrics for determining success in the α game.

<u>Case Study</u>: "*Designed to study intensely one set (or unit) of something; for e.g. programs, cities, counties, worksites-as a distinct whole, with the goal of understanding the set as a distinct whole in its particular context. A case study reveals the process and outcome at certain sites and the way in which these interrelate. Case studies are conducted primarily using qualitative techniques, but do not exclude quantitative data." (van Vleet, 2004)*

<u>Collusion</u>: "*A secret agreement between two or more parties for a fraudulent, illegal or deceitful purpose"* (van Vleet, 2004). Or as defined by the OED as "*secret agreement or understanding for the purpose of trickery or fraud*", is generally considered to be reprehensible and is usually illegal in a free market system, because of the economic distortions introduced into the market.

<u>Dutch Auction</u>: *"A type of auction where the auctioneer begins with a high asking price which is lowered until some participant is willing to accept the auctioneer's price, or a*

predetermined reserve price (the seller's minimum acceptable price) is reached" (van Vleet, 2004).

Economic Winner: "*An individual who generated the highest average returns."* Panchal (2007) coined this term to indicate a more successful player in the α game. An economic winner makes no direct difference to the ω game for the υ player where the υ player has an objective of minimizing the average bid for the game. The υ player sees the average price for purchases and a distribution of prices.

Economic Loser*:* *"An individual who generated the lowest average returns."* Panchal (2007) coined this term to indicate a less successful player in the α game. An economic loser makes no direct difference to the ω game for the υ player where the υ player has an objective of minimizing the average bid for the game.

Efficiency: The ratio of the output to the input of any system.

Game: a series of jobs for the construction of a reinforced concrete floor slab, each game lasts approximately 8 to 10 weeks in game play time, with each round of the game modelling a week and occurring in a 20 minute period, with 15 minutes of bid time and 5 minutes of build time.

<u>Game Theory</u>: A formal analysis of conflict and cooperation among intelligent and rational decision makers.

<u>Herfindahl Index:</u> *"a measure of the size of firms in relationship to the industry and an indicator of the amount of competition among them. It is defined as the sum of the squares of the market shares of each individual firm. As such, it can range from 0 to 10,000, moving from a very large amount of very small firms to a single monopolistic producer. Decreases in the Herfindahl index generally indicate a loss of pricing power and an increase in competition, whereas increases imply the opposite. The Department of Justice considers Herfindahl indices between 1000 and 1800 to be moderately concentrated and indices above 1800 to be concentrated. As the market concentration increases, competition and efficiency decrease and the chances of collusion and monopoly increase."* (van Vleet, 2004).

<u>Job:</u> A work unit, in this case a reinforced concrete slab for a home builder, taking 5 working days to construct.

<u>Loan Amount</u>: It is a bank loan or a guarantee taken by the bidder with the purpose of increasing the bidders' job capacity. The cost is $500 per job.

Loss: negative return applied to a business undertaking after all operating expenses have been met.

Lump Sum Offer: A tender submitted for a lump sum amount in the game assumed to be for a fixed price.

Pre-Qualified: The process of declaring competent or capable or to certify in advance. The purpose of pre – qualified is to maintain the economic competition.

Profit: The return received on a business undertaking after all operating expenses have been met.

Profit Efficiency: It is the ratio of the profit made to the number of jobs won. This is one of the postulated metrics for determining success in the α game.

Purchaser: Either an owner or owner's representative who organizes the bid or tender document.

Reverse Auction Bidding: "*It is a single or multiple-item, open, descending-price auction. The initiator specifies the opening bid price and bid decrement. Each bidder submits a successively lower bid. At the end of the auction, the bidder with lowest bid value is being considered as a winner"* (van Vleet, 2004).

Second Bidder Issue: "*It has been postulated that the lowest bidder in Reverse Auction Bidding is seeking to undercut the second bidder by the smallest quantifiable fragment, if the bidder* *understands the principles of tacit collusion"(Chaudary, 2009).* The hypothesis forms the basis for future research.

Sealed Bidding: "*In this type of auction, all bidders simultaneously submit bids in such a way that no bidder knows the bid of any other participant. The highest/lowest bidder is awarded the contract at an agreed price, all other things being equal"* (van Vleet, 2004).

Sherman Antitrust Act: *"The act, based on the constitutional power of Congress to regulate interstate commerce, declared illegal every contract, combination (in the form of trust or otherwise), or conspiracy in restraint of interstate and foreign trade. According to Nichols (2010), the problem is tacit collusion does not fit within the meanings of the act, thus leading to the debate about the legality of RAB between contractors who consider it illegal or unethical and economists who accept the converse."*

Tacit Collusion: *"Seemingly independent, but parallel actions among competing firms (mostly oligopolistic firms) in an industry that achieve higher prices and profits, much as if guided by an explicit collusion agreement. Also termed implicit collusion, the distinguishing feature of tacit collusion is the lack of any explicit agreement. The key is that each* *firm seems to be acting independently, perhaps each responding to the same market conditions, but the end result is the same as an explicit agreement. This should be contrasted with explicit or overt collusion that does involve a formal, explicit agreement. Tacit collusion is observed in Reverse Auction Bidding, and is potentially related to the Second Bidder Issue" (Chouhan, 2009).* Nichols (2010) postulates that the α game has been observed and misunderstood as tacit collusion, in reality it can be viewed potentially reviewed as an aggressive player seeking a better than average return from the profit distribution resulting from the α game.

Traditional Bidding: "*In this type of auction all bidders simultaneously submit bids in such a way that no bidder knows the bid of any other participant. The highest/lowest bidder is assumed to be awarded at the price submitted provided no other contracts opened on the decision process" (*Chaudary, *2009).*

Winners Curse: "*Problem faced by uninformed bidders or poor game players. For example, in an initial public offering uninformed participants are likely to purchase larger* *allotments of issues that informed participants know are overpriced."*

GAME TYPE

Consider a Reverse Auction Bidding game where the υ player is willing to accept bids of the type shown in equation (1):

$$\mathrm{B}_j = \mathrm{K} + \Xi_j \Gamma, \tag{1}$$

Γ represents the upper limit the υ player is prepared to pay in the game above the nominal minimum bid amount K. A negative Ξ_j represents a loss on direct costs to the λ_i player who makes this type of bid, and enough of these bids will lead to a bankrupt player. The concept of Γ can be attributed to Feigenbaum (Nichols, 2010), who considered there had to be an upper limit everyone was prepared to pay for a service or good.

The bidding period for each game lasts for a set time, τ, in this case it is 15 minutes. The total cost for υ player is shown in equation (2):

$$\mathrm{B}_v = \sum_{j=1}^{n} \mathrm{B}_j, \tag{2}$$

This total cost is based on the accepted lowest bid for each job, where the λ player submitted a valid bid. Each λ_i player then has a unique set of bids and a unique set of jobs, with a total return to the λ_i player defined by a simple summation.

REVERSE AUCTION BIDDING

Reverse Auction Bidding (RAB) is a purchasing process for a good or services. RAB was first used in the manufacturing sectors, but this method is now used in the construction industry. Figure 1 shows a typical process for a Reverse Auction System. The process continues until a preset trigger occurs, in some situations it is passage of a time period since the last bid, or in the case of this research the bidding period is set at 15 minutes for practical experimental reasons.

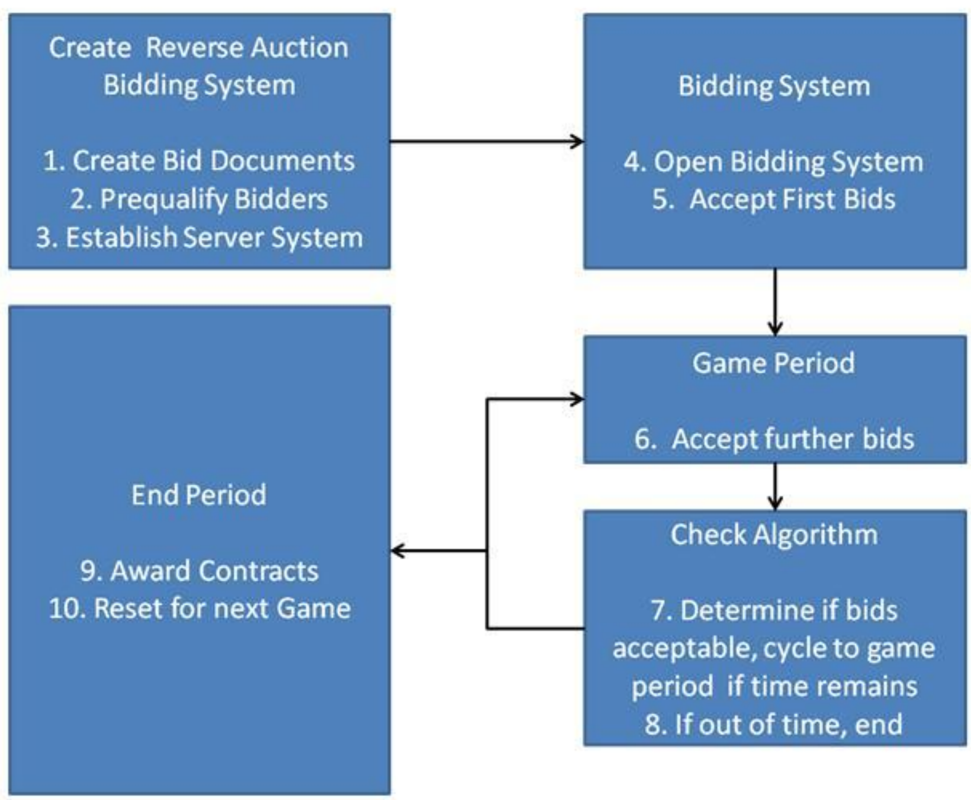

Figure 1 Reverse Auction Bidding General Algorithm

REVERSE AUCTION BIDDING - THE RESEARCH GAME

van Vleet (2004) developed a simple construction scenario for the Reverse Auction Bidding game. van Vleet's unpublished professional paper is not generally available, so the game development stage of van Vleet's research work is outlined in this section. The construction work was assumed to occur in and around Houston at six locations as shown in Figure 2.

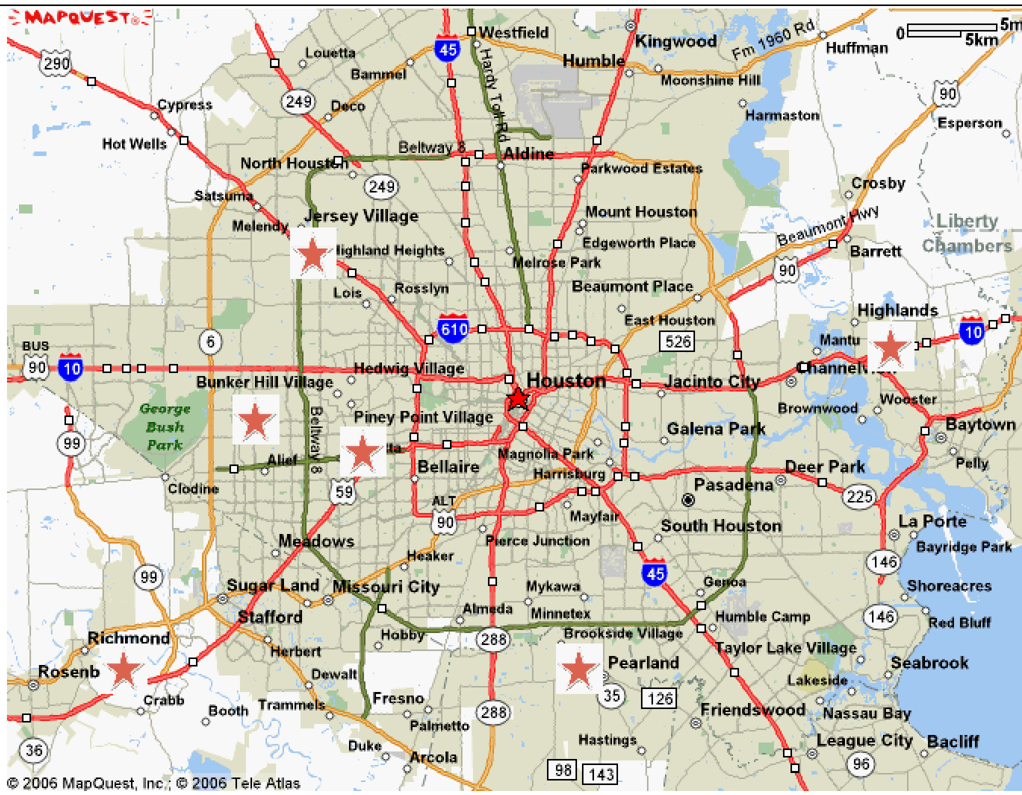

Figure 2 Construction Site Locations in Houston (after MapQuest, 2006)

Table 1 lists the six locations shown on Figure 2 above. The distance in kilometres from the purchaser's office in Sugar Land is given in the table. The assumption for each of the λ_i players is that each player is one of several sub-contractors that this homebuilder, the υ player, utilizes to construct the foundations for simple residential single-family homes. The work is repetitive, unchanged in terms of scope from week to week, other than the number of houses started per week. The game ignores the obvious problem that the υ player should establish a long-term stable price. The use of a simple slab is merely a guide project; the assumption is that some work type would follow this market pattern. This issue of a long-term stock price is obviously not acceptable to a RAB based purchaser, υ player, who is seeking a competitive advantage. In seeking the competitive advantage, the υ player creates α game. The α game has a Ξ distribution that represents a potential net return to each λ_i player; who are seeking a competitive advantage within the Reverse Auction Bidding system. The key point is υ player creating the α game. The α game provides a mechanism for the canny λ_i player to seek to maximize their returns, whilst co-operative play is in the interest of λ players in the ω game. Reverse Auction Bidding is a good game, but a less than satisfactory purchasing system for most goods and services.

Table 1
Location of the Construction Sites in Houston

Site #	*Location of Development*	*Distance from Sugarland (kilometres)*
1	Brookside Village	41.6
2	Piney Point Village	24
3	Highlands	70.4
4	Jersey Village	40
5	Bunker Hill Village	27.2
6	Richmond	14.4

The work is repetitive, as is usual for a production homebuilder, which simplifies the production process. The production builder builds only one type of home and hence requires each contractor to pour only one type of slab. All λ_i players have been prequalified and only price matters, as is normal in this type of bidding system. The key assumption is that each Monday, the υ player, posts the jobs that they are going to start that week. The data included is where each job is located.

All information is given to the bidders through an ASP based web site (Kingsley-Hughes, Kingsley-Hughes, & Read, 2004). The web site was developed by Kim (2004) for van Vleet, and has been maintained by Nichols (2010). This study uses the Microsoft Access database generated by van Vleet.

Gregory (2006) encountered significant problems with a study involving ten participants using the Access database, as a result of Access' limitations on number of connections. Gregory's study was undertaken on a Microsoft SQL database developed by Wellington (2006), which overcame the limitations. SQL database systems can generate a significant quantity of data, which creates a computer science problem, now commonly termed 'Data rich – analysis poor'. The current research problem for future studies is development of SQL queries to analyze the data. A domain location was created on a Texas A&M University server to host the Reverse Auction Bidding system. Six unique participant names were created for the study: Driver, Pliers, Concrete, Rove, Copper, and Log. The user names and associated passwords were located on in Microsoft Access data table, which could be accessed through the login screen. The use of the unique participant names is to protect the identity of the bidders in accordance with the IRB requirements for this type of study. These specific login name and password allowed the players to enter the website. However, it limited player access to the information that was relevant only to their bidding process.

Figure 3 shows the login screen for van Vleet's study.

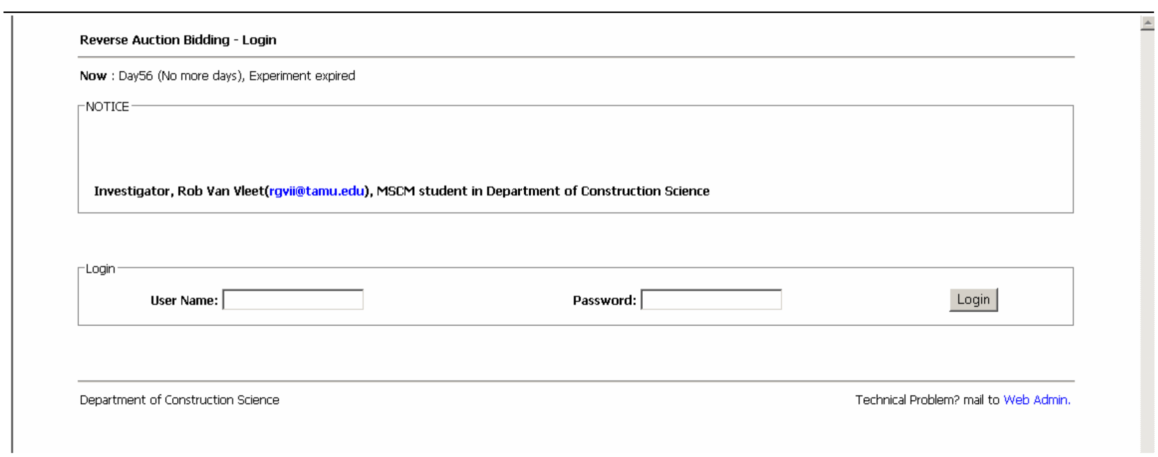

Figure 3 Reverse Auction Bidding Login Screen

Figure 4 shows a sample data screen for one of the bidders. The screen shows the data for the fourth week. The screen shows one completed job, four jobs in progress and two current bids.

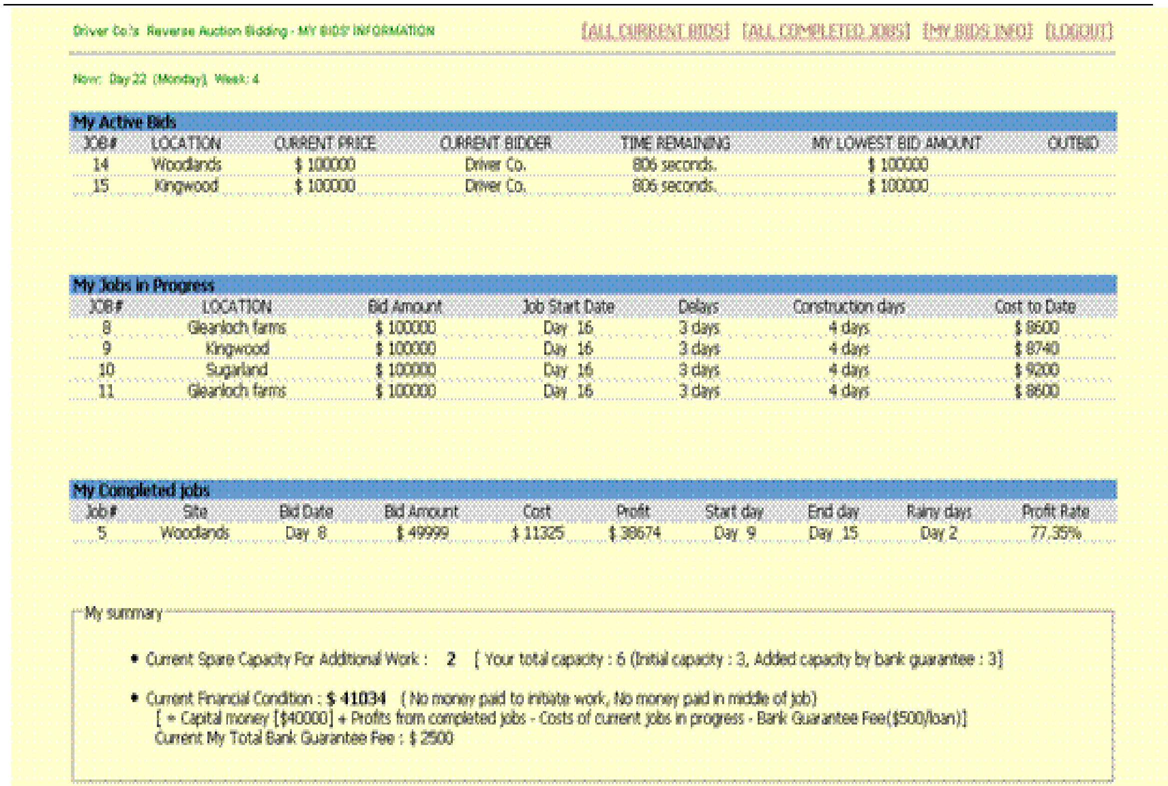

Figure 4 Reverse Auction Bidding - Sample Data Screen

This λ_i player's financial information is provided under the category defined as My Summary. The information provided was current calculated cash assets, capacity for additional works including jobs with bank guarantees and cumulative loan charges up to date. This summary of the current financial condition summarizes the working capital information available to the participants. It is calculated by deducting costs of current jobs and bank loans from the profits of completed jobs. van Vleet did not want the bidders to have to spend time determining their costs or the potential profits each was making with a particular bid, so this website provides significantly more information than would be normal. This is not an issue as the υ player is mythical, and thus cannot observe the games progress. The cost data provided for each site as shown in Table 2.

Table 2
Site Development Costs for Each Slab

Site #	*Travel Cost ($)*	*Delivery Cost ($)*	*Total Cost($)*
1	858	624	1482
2	495	360	855
3	1452	1056	2508
4	825	600	1425
5	561	408	969
6	297	216	513

The base cost for the slab is $10,000. Table 3 lists the default variables for the Reverse Auction Bidding web site.

Table 3
van Vleet's Default Variables for Game

Component	*Unit*	*Amount*
Bank account of each contractor at start of the game	$	40,000
Job cost	$	10,000 for the slab cost, travel costs delivery charges
Total time of competition	Weeks	8
Maximum work capacity at outset of the game	Jobs	3
Loan amount for adding bid capacity	$	500
Each job contract time	Days	5
Work week	Days	6 (Monday to Saturday)
Chances of rain delay	Percent	30
Construction cost accrued	-	Daily
Payment for work	Day	5^{th}
Bidding time	Minutes	15

The basic scenario developed by van Vleet was discussed with Nichols (2010), who pointed out the need to maintain a simple system. Significant advances have occurred with the web site; however, van Vleet established all of the critical factors for the game. The timing of each round of the game, representing a week, was set at 20 minutes, with 15 minutes of bid time and 5 minutes of construction time. One subsequent game modelled on a ten-minute week proved to be a disaster to play as a game and this idea was abandoned (Nichols, 2010). Stable economic conditions are assumed to exist for the duration of the work.

A disturbance in the form of rain delay was included in the game. The assumption of a set of Houston sites, with construction occurring in the May to June period, provides a significant probability of rain in any one week. Chouhan (2009) provided a drawing (Figure 5) showing the rain probability obtained from a NOAA web site.

van Vleet's assumption was an average of 30% rainfall probability per day. A single day of rain typically did not delay completion of the work, but two days or a carryover job from the previous week impacted the bidding capacity. A job carried over from the previous week reduced the bid capacity by one site.

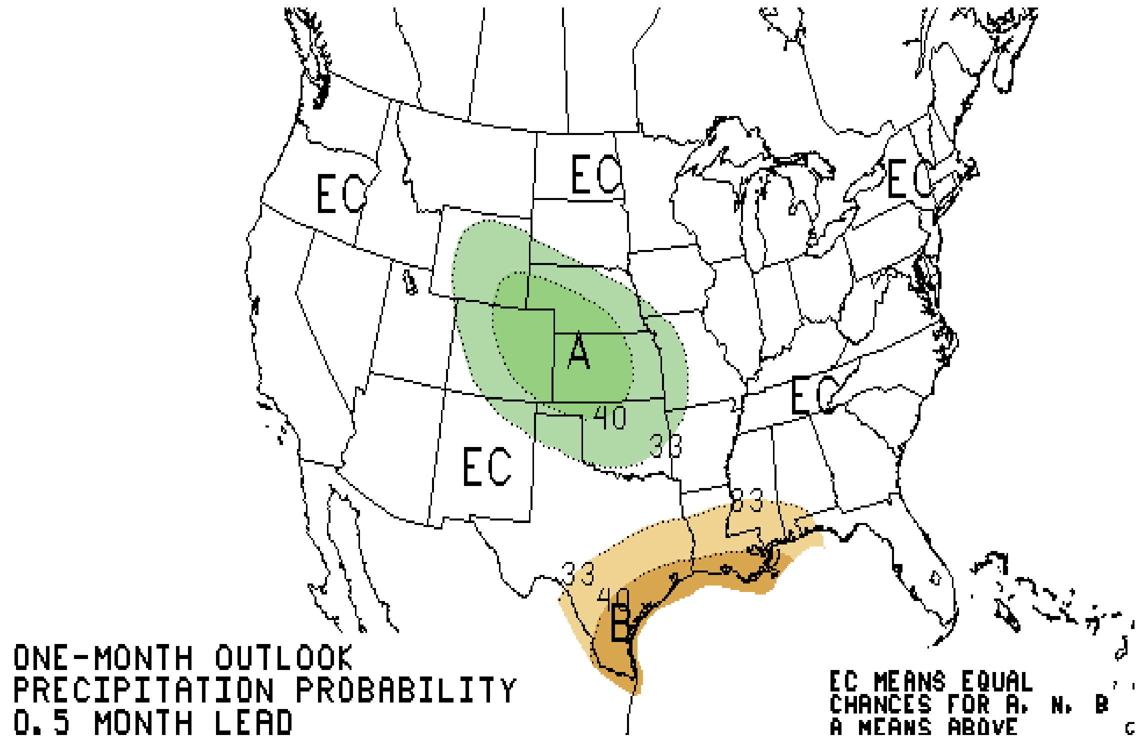

Figure 5 Rain Probability in Houston (after NOAA, 2009 and Chouhan, 2009)

There will be no additional charges for any delays, nor is the contractor penalized for the delay in cost terms as the contractor is assumed to make reasonable arrangements with the workforce for rain delays, these delay costs are assumed to be covered in each player's bids. The issue with the rain delay is the likely concurrence of rain on all sites, which is not allowed for in this method of rain allocation.

Table 4 presents the rain delay data for the first week of the Reverse Auction Bidding game. A one (1) indicates rain on a particular day at a particular site, resulting in a delay to the contract completion.

Each bidder had a nominal capacity for three jobs per week. Rain delays could reduce this capacity, theoretically to zero, although statistically this is improbable.

Table 4
Rain Delay Data for First Week

Day	*Site 1*	*Site 2*	*Site 3*	*Site 4*	*Site 5*	*Site 6*
Monday	1	0	0	0	1	0
Tuesday	0	1	1	0	0	0
Wednesday	0	0	0	0	0	0
Thursday	0	0	1	0	0	1
Friday	1	0	0	0	1	1
Saturday	0	0	0	0	0	0

A mechanism was provided for each bidder to increase their capacity to bid as shown in Figure 6.

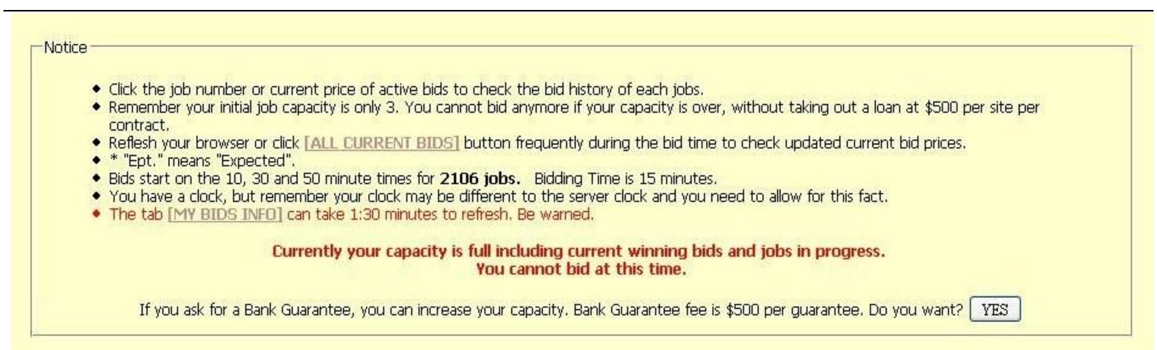

Figure 6 Bank Guarantee Screen

This is a reverse auction process; the protocols are coded in the ASP program to ensure that only a lower bid value is accepted. An erroneously high bids results in Figure 7 being displayed, which warns that entering a higher bid amount than the current lowest bid amount is not allowed.

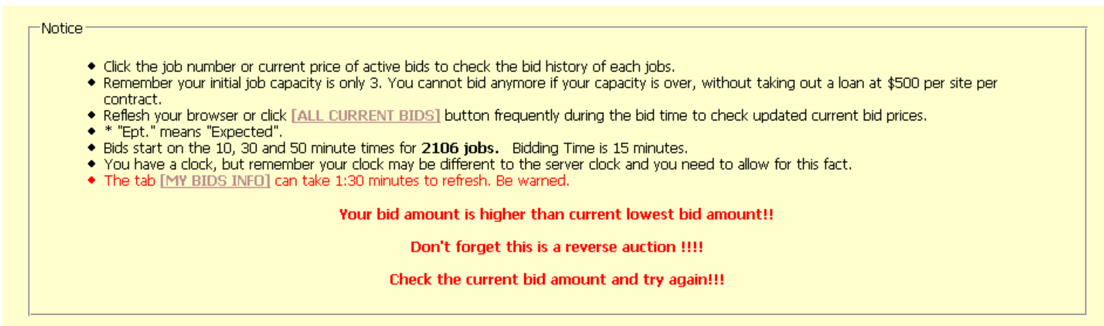

Figure 7 High Bid Screen

A game typically lasts from three to four hours. Players become fatigued after about nine games.

BIDDING TRENDS

Chouhan (2009) postulated that four trend period could be observed in a Reverse Auction game. Figure 8 shows the job data from Chouhan's study. Job identifiers are unique to each case study, with Chouhan's study numbered approximately 490 to 560. This type of change in the bidding has been observed in previous games to a varying degree (Chaudary, 2009; Shankar, 2005; van Vleet, 2004). The observations shown in Figure 8 have been statistically analysed to confirm the apparent visually observed pattern.

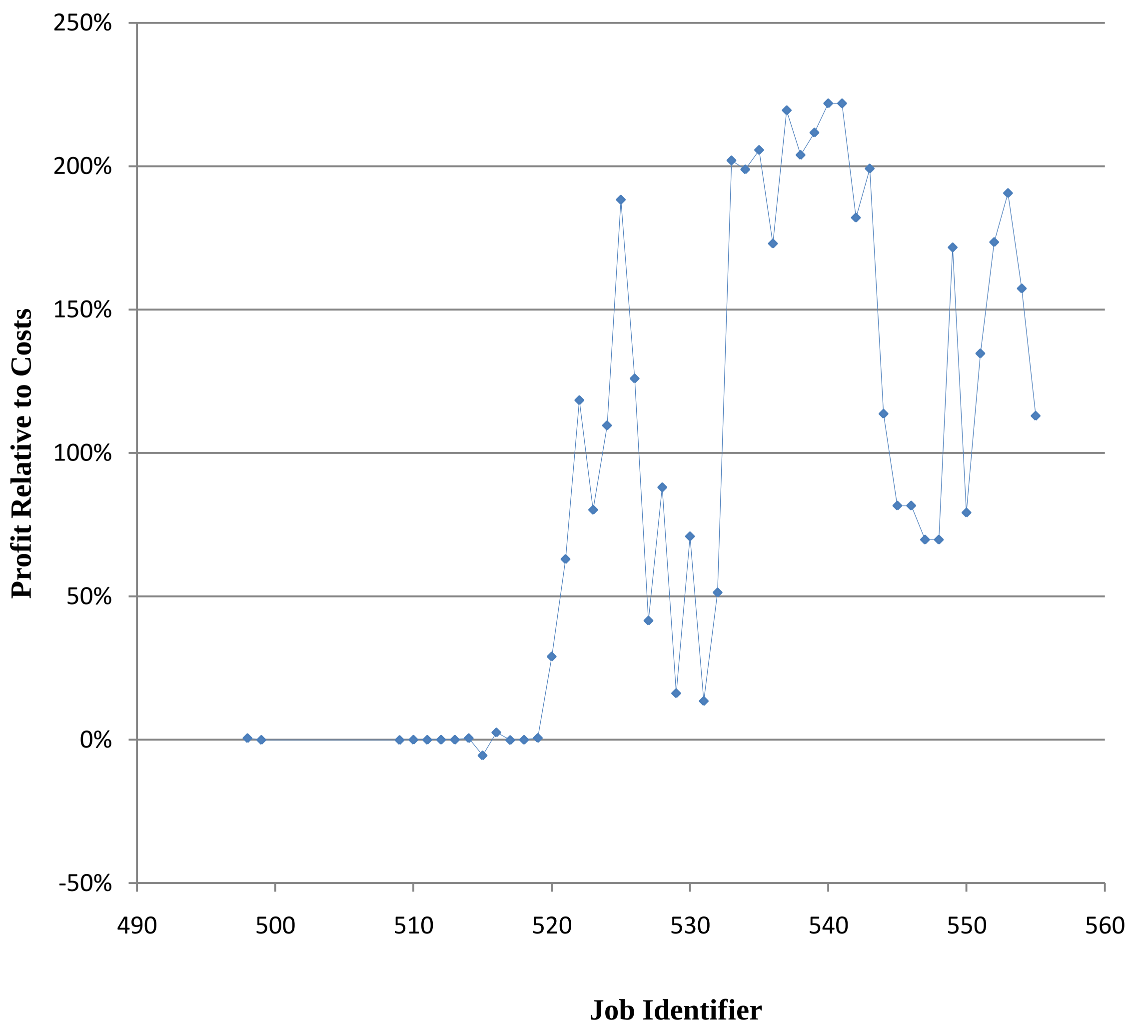

Figure 8 Reverse Auction Data Job Profit Relative to Cost from Chouhan (2009)

Figure 10 shows a trend line added to the data in Figure 8. The job identifiers are reset to commence at one. The trend-line shows an increase in the average job as the job number increases. The R^2 coefficient at 0.459 indicates a positive pattern, although one with significant variation. Chouhan postulated that particular periods of play in the Reverse Auction Bid data indicates different stages in the development of the game play.

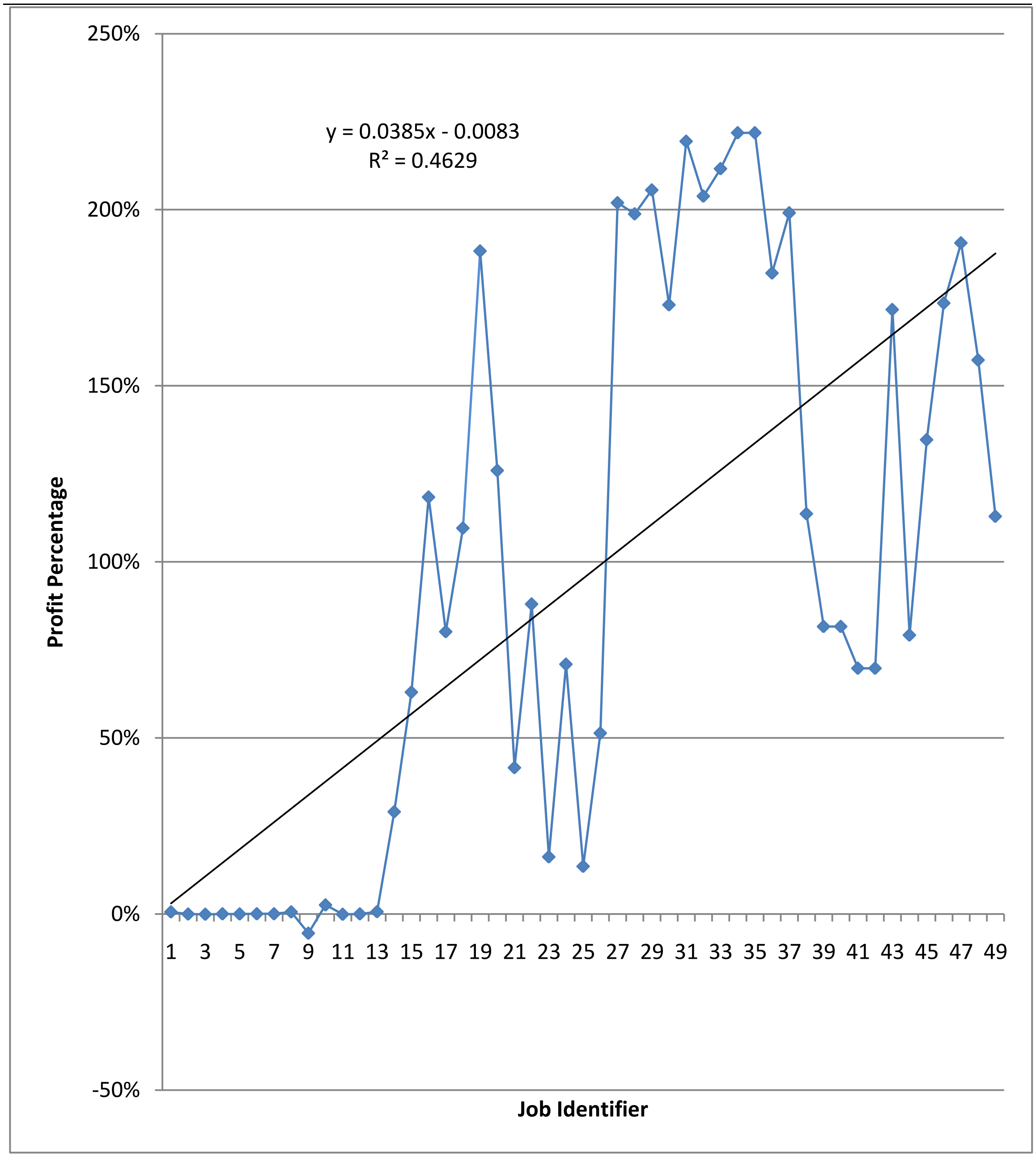

Figure 9 Reverse Auction Bid Data from Figure 8 with Trend Line Added

Rogers (2010) suggested a fifth order polynomial to fit the data. Figure 10 shows this type trend line fitted to the data. The trend line picks up the characteristics of the data, but it's smooth and continuous form limits the ability to fit rapidly changing data.

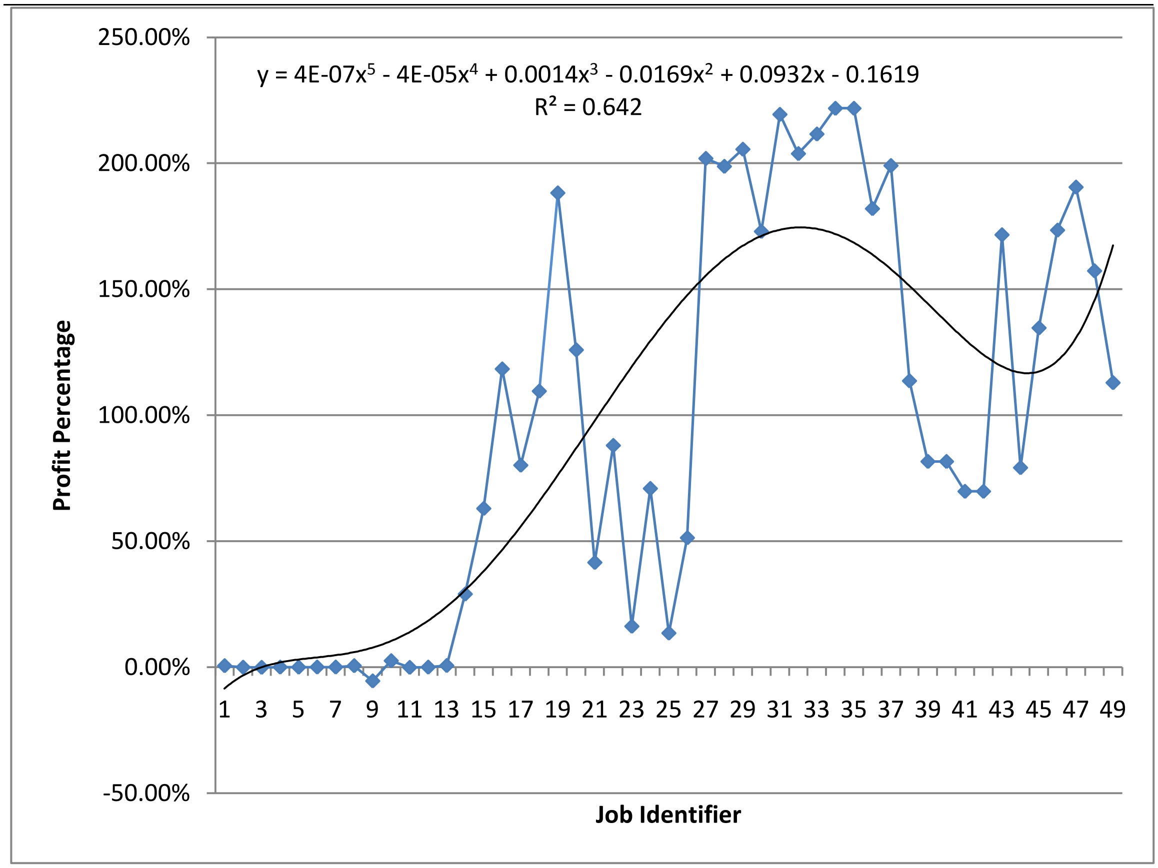

Figure 10 Reverse Auction Bid Data from Figure 8 with Trend Line

The theory postulated is outlined in summary form in Table 5. Similar observations have occurred in other case studies. Nichols (2010) suggested that the learning period occurs with new participants who have no prior experience in bidding and bid low with the mistaken assumption that this is the best strategy for playing the game. At some stage, a λ_i player determines that some jobs are not being bid as competitively as others are and obtains a job at higher profit. Some or all of the other λ_i players discover the ability to increase their returns, resulting in a significant average increase in price to the υ player, followed by a brief competitive period and then a longer period of higher profits. This is a future research area.

Table 5
Chouhan's Postulated Trends in Bid Period

Job Identifier Number	*Description of the Trend Period*
0 to 13:	Learning
14 to 21:	Discovering
22 to 27:	Competitive
28 to 49:	Profit Gain

The theory postulated by Chouhan can be tested using the Student’s t Test. Table 6 lists the results for the Student’s t test analysis and cross analysis of the four postulated stages.

Table 6
Student's t Test Analysis of the Trend Periods

Stage	1	2	3	4
1	-	-5.30	-3.9	-14.1
2		-	2.42	-2.58
3			-	-6.82
4				-

Student’s t Test is a standard test to determine if two sets of numbers (Borowski & Borwein, 1989; Weinberg & Schumaker, 1964) are derived from the same base data set. Six Student’s t tests were completed on data shown in Figure 8. The results presented in Table 6 show that the trend periods are represented by number sets that are not derived from the same base set. At least for this data set, Chouhan’s postulate holds at the 5% level of confidence.

COMMENTS

Reverse Auction Bidding is a relatively new system of purchasing goods and services. As with all new systems, it has its proponents and those who are antagonistic to the system because of the perceived interference that may occur in the process. The long-term study at TAMU in the Construction Science Department is attempting to investigate some of the main issues with Reverse Auction Bidding.

CHAPTER III

METHODOLOGY

INTRODUCTION

This research work is a review of the first case study on Reverse Auction Bidding completed by van Vleet in 2004. This chapter outlines the original study procedure, the data collected and the initial analysis completed by van Vleet. The basic methods are common to all Reverse Auction Bidding studies completed at Texas A&M University.

ORIGINAL STUDY PROCEDURE – UNIQUE FEATURES

The basics common to all Reverse Auction Bidding games was presented in the Literature Review. The key element distinguishing the different games is the number of players and the distribution of the number of jobs in each week of the game.

The number of jobs in a week is determined using a roll of three dice, providing a truncated approximately normal distribution. The first case study had five players so that most weeks the bidders have spare capacity, which provides the competition driving mechanism. This study used five participants, which provides a Herfindahl index of 2000. This number of participants is at about the limit at which the Justice Department considers is concentrated, although with five bidders of equal capacity it should not be considered non-competitive. An integer count of 3 to 18 from the die roll is not normally distributed because of the truncated range and the integer nature of the count. The number of possible combinations with three dice are 216. A plot of the Gaussian distribution (Weinberg & Schumaker, 1964) against the probability for each the sixteen combination of numbers from 3 to 18 available from a set of three dice is shown on Figure 11. The differences are minor and for all intents and purpose not statistically significant for the purposes of this research.

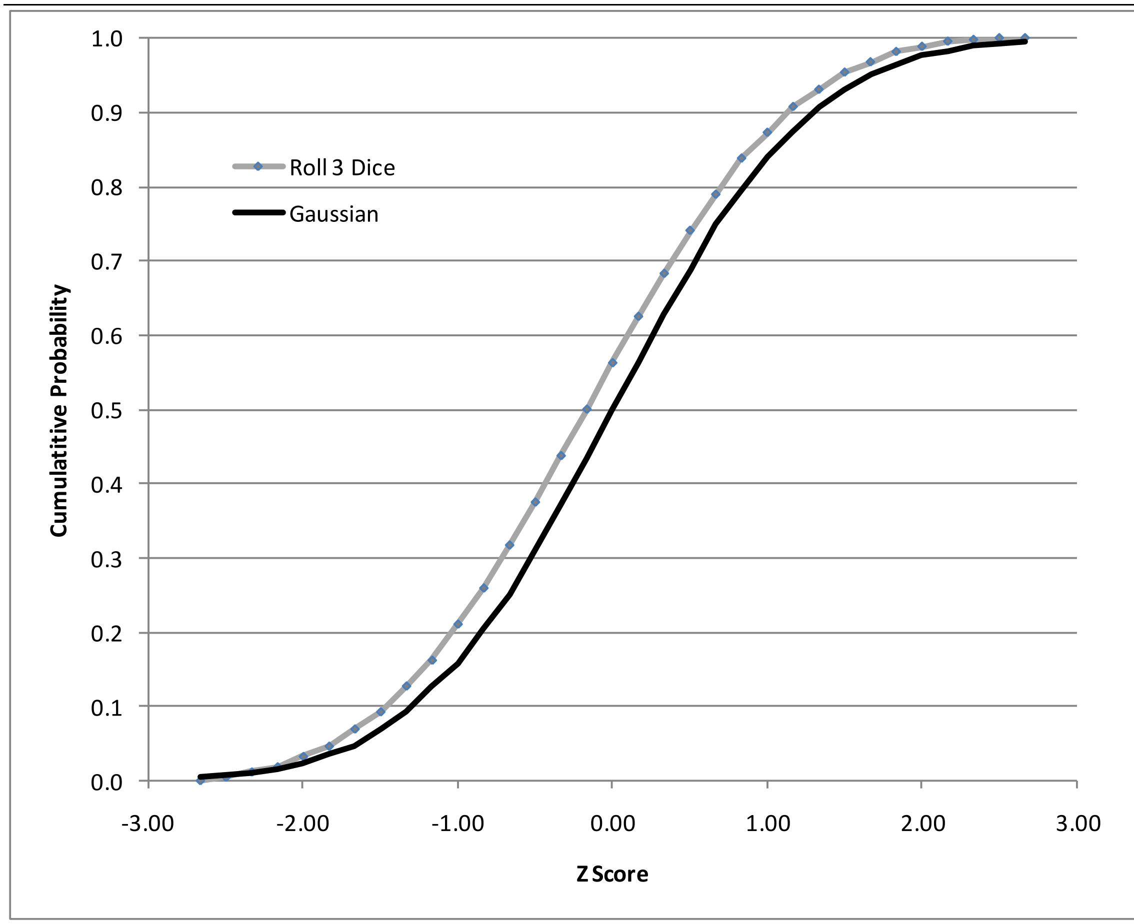

Figure 11 Probability of the Job Data Distribution per Week

The weekly distribution of jobs used in this game is listed in Table 7. The critical issue is the limited number of weeks for the game, assuming the mean number of jobs at 10.5 as shown in Table 7, a game would need to cover 21 weeks to cover an approximation of the probability distribution for three dice.

Table 7
Number of Jobs per Week and Descriptive Statistics

Week	*Jobs*
1	13
2	6
3	11
4	10
5	11
6	14
7	11
8	Not used (11)
Mean	10.875
Standard Deviation	2.54
Total	76

The mean is slightly higher than the true mean of three dice and the standard deviation is about 76 % of the true standard deviation. The data set lacks the higher values covered in a full 216 weeks. The real game terminated at Week7. As this was the first case study, it was considered important to randomly number the sites and determine the site identity number. The simplest way to do was to randomly number the site from 1 to 6. This was achieved using a single dice. Costs such as traveling and delivery related to the site, were assumed to be proportional to the distance of the site with respect to Sugar Land base of the υ player.

ORIGINAL STUDY PARTICIPANTS AND GAME PERIOD

The auction was conducted using 5 participants. Each participant was briefed about the website, rules and regulations. The name of the participants are not disclosed due to IRB confidentiality requirements. Each participant was given an logon identity and password. Each was isolated from other participants to avoid communication. The process continued for 3 hours and then all participants came together to discuss the results.

VAN VLEET DATA AND ANALYSIS

692 bids were captured by the ASP system over the course of the experiment, for the 76 jobs. The data from the findings of the project was analyzed using SPSS 13.0 (van Vleet, 2004). Van Vleet’s first step was to gain an overall understanding of the project, checking to analyze any apparent trends and looking for possible price outliers that may adversely affect the findings. The Contract job prices are shown in Figure 12.

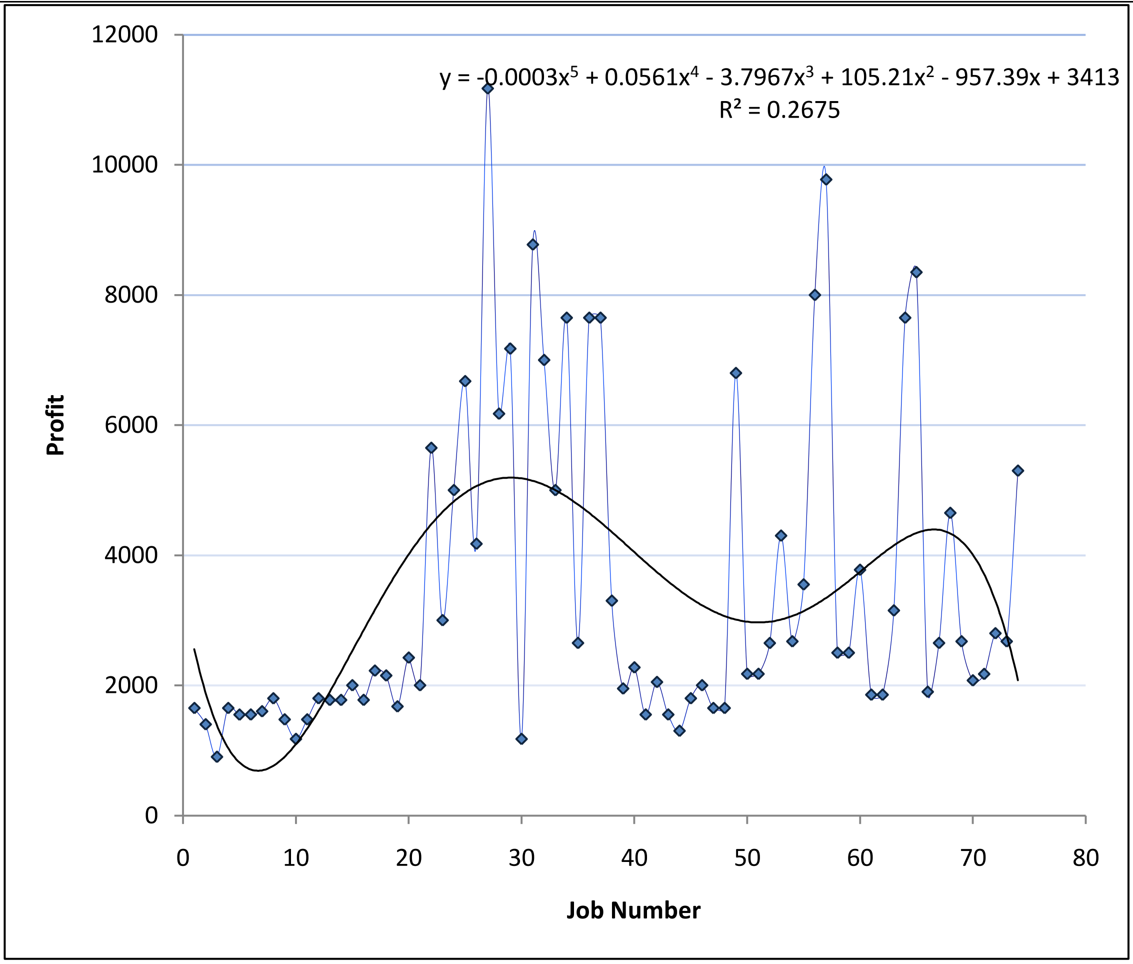

Figure 12 Profits for the 76 Jobs

The figure is a modified by removing two jobs (job 24 and 25 with profits of \$18550 and \$14550), which were obscuring the main features of the graph.

A fifth order polynomial was fitted to the data, to gain some understanding of the relative changes in the profit with time. The polynomial shows the underlying pattern in the profit data, as postulated by Chouhan.

The game theory established for this Reverse Auction Bidding included an equation for the form of the contracts, as shown below.

$$B_j = K + \Xi_j \Gamma, \tag{2}$$

Γ represents the differential upper limit the υ player is prepared to pay in the game above the nominal minimum bid amount K. In reality, K is an array with a unique entry for each site. A negative Ξ represents a loss on direct costs to the λ_i player who makes this type of bid, and enough of these bids will lead to a bankrupt player. Ξ represents a normalization of the amount the υ player has had to accept under the rules of the game. Ξ allows a direct comparison of the results from different games, without becoming lost in the argument about how high an amount a real υ player would accept for the bids. The assumption is the distribution of Ξ represents a real bidding scenario. The data from Figure 12 has been re-cast in the form of Ξ and is shown in Figure 13.

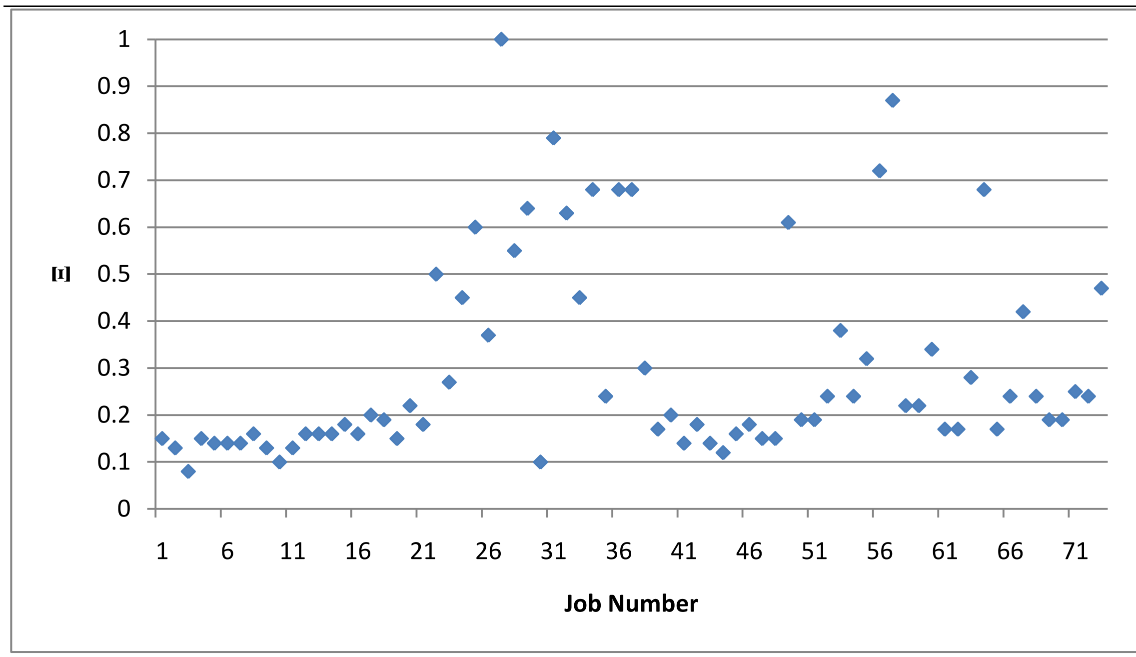

Figure 13 Normalized Profit Data

Table 8 provides a summary of the results in histogram form.

Table 8
Normalized Profit Results

Ξ *Range*	*Number*
Less than 0	0
0 to 0.1	3
0.11 to 0.2	35
0.21 to 0.3	13
0.31 to 0.4	4
0.41 to 0.5	5
0.51 to 0.6	2
0.61 to 0.7	7
0.71 to 0.8	2
0.81 to 0.9	1
0.91 to 1.0	1

Figure 14 shows a histogram of the Ξ; results shown in Table 8.

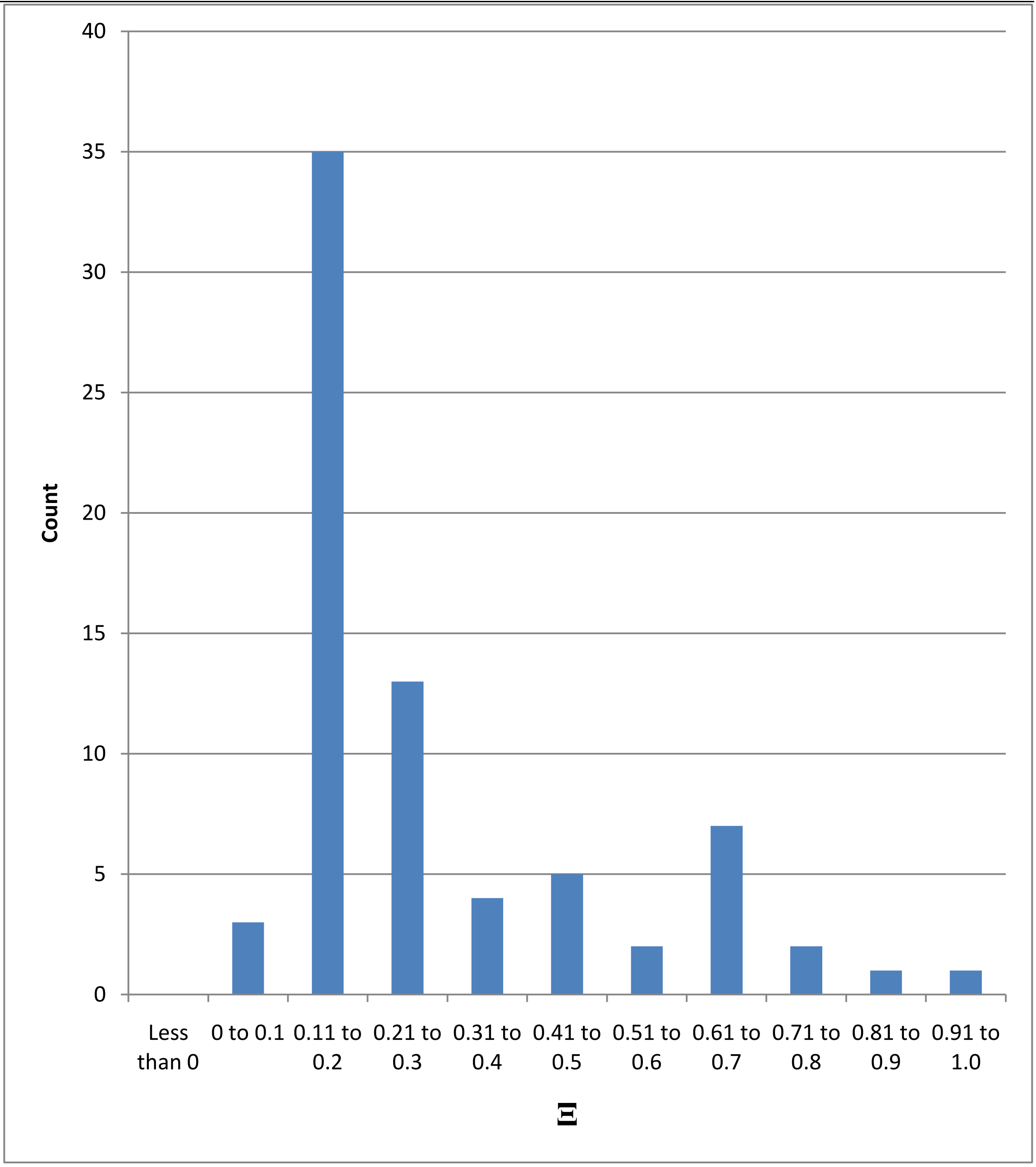

Figure 14 Shows a Histogram of Ξ and Its Frequency.

The results show a non Gaussian distribution that will be the subject of future studies. Figure 15 shows the percentage of the total number of jobs won by each participant.

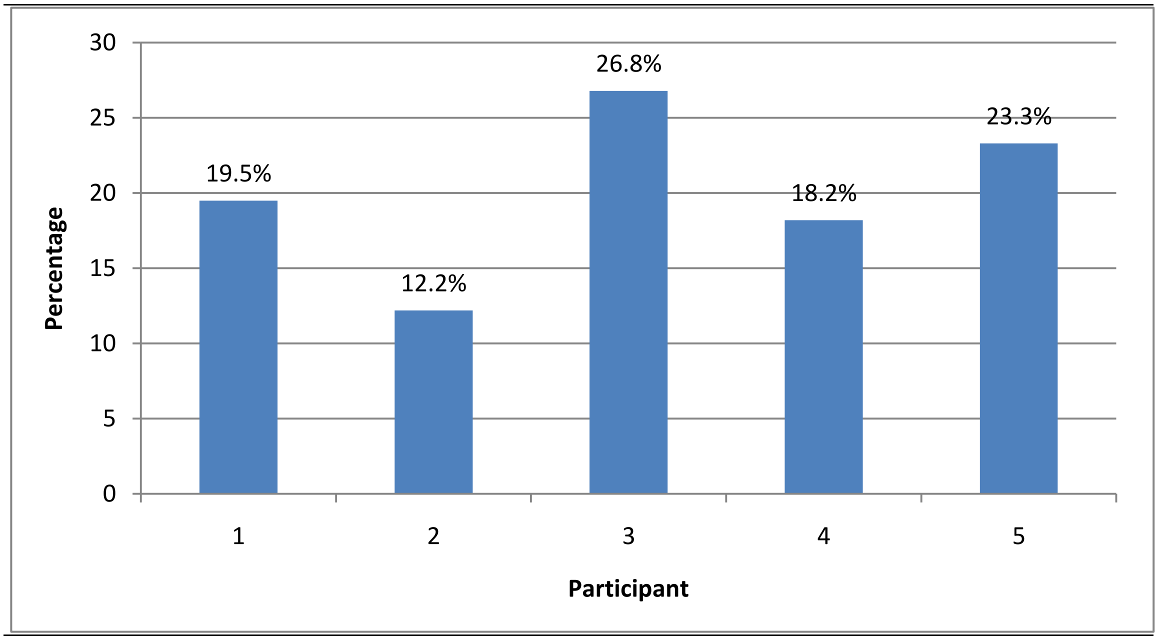

Figure 15 Jobs won by Participants as a Percentage

COMMENTS

The key elements of van Vleet's methods and research results are summarized in this methodology chapter. The subsequent analysis uses this data.

CHAPTER IV

RESULTS

INTRODUCTION

The research objectives for this study are:

1. Establish plots of the bidding data
2. Compare the bidding patterns shown in the plots with time for all bidders
3. Determine if evidence exists in the bidding data to confirm the existence of the ω game and does it represent some form of collusion
4. Compare the returns of the different bidders in the α game to determine if there are differences in bidding returns and does it represent some form of collusion

The results presented are the trend period comparison, descriptive statistics of the bid data, descriptive statistics of the contract data, bid period comparison, and differential bid data. The results presented are used to provide:

1. Trend period comparison to determine if the van Vleet data shows elements of the trend periods postulated by Chouhan, to provide data to answer the second objective
2. Descriptive statistics for the bid data to provide data for the first objective
3. Descriptive statistics for the job cost data to provide data for the first and third objectives
4. Bid period statistics to provide data on the temporal distribution of bidding during the game period to provide data for the third and fourth

objectives and establish differential bid statistics related to the last and the second last bid data to provide data for the third and fourth objectives

TREND PERIOD COMPARISON

Chouhan postulated a set of four different periods in the game as presented in Table 5 (page. 31). Figure 12 shows the set of job profits for van Vleet's study. Four trend periods have been established for the data shown on Figure 12.

Table 9 presents the estimated job numbers representing the limits of the four trend period to match those periods postulated by Chouhan.

Table 9
Trend Periods in van Vleet Data

Description of the Trend Period	*Job at Start of Period*	*Job at End of Period*
Learning	1	20
Discovering	21	40
Competitive	41	51
Profit Gain	52	76

A descriptive comparison can be made between the trend periods observed in the two studies, refer to Table 10. The graphs looked similar but the average return for

Chouhan's study were higher than van Vleet's. No further comment can be added to this observation, other than to strongly suggest this is an area of future research.

Table 10
Comparison of the Trend Periods for the Two Studies

Trend Description	*Chouhan*	*van Vleet*
Learning	Evident	Highly similar
Discovering	Evident	Highly similar
Competitive	Evident	Similar, not proven
Profit gain	Evident	Quite similar

The theory postulated by Chouhan can be tested using the Student's t Test. Table 11 lists the results for the Student's t test analysis and cross analysis of the four postulated stages in van Vleet's data.

Table 11
Student's t Test Analysis of the Trend Periods of van Vleets Data

Stage	1	2	3	4
1	-	-7.3	-0.96	-4.74
2		-	7.02	2.98
3			-	-4.32

The results are not as distinct as Chouhan’s and the correlation evident between the first and third trend periods should be the subject of review using other case studies. The statistical observation between the first and the third stage suggests that the competitive period is as competitive as the learning stage in this game.

DESCRIPTIVE STATISTICS OF THE BID DATA

The bid data has been summarized for each week in Table 12.

Table 12
Number of Jobs and Number of Bids per Job per Week

Week	*Jobs/week*	*Bids/week*
1	13	130
2	6	100
3	11	63
4	10	74
5	11	117
6	14	109
7	11	99
Total	76	692

The results show a tolerably constant rate of bidding for the game period. Table 13 lists the number of bids made and the number of jobs won in the game by each of the bidders.

Table 13
Different Factors for the Bidders

Rank	*Participant*	*No. of Bids*	*Jobs Won*
1	5	218	17
2	3	92	22
3	4	167	13
4	1	147	16
5	2	70	8

Profit data is presented in Table 14. The ratio between the highest profit and the lowest profit is 3.7.

Table 14
Profit Data

Rank	*Participant*	*Loan ($)*	*Profit ($)*
1	5	11,000	91,673
2	3	8,500	59,170
3	4	2,000	53,025
4	1	4,000	37,559
5	2	2,500	24,650

The data in the tables is sorted in order of highest to lowest profit return for the five participants. Participant number 5 had the highest profit, whilst making the greatest number of bids. Participant number 5 won jobs at a higher overall profit rate when compared to the next highest return by participant number 3.

These results point to a future research area. The trend-line on the figure has been assumed to not pass through the origin. A R^2 of 0.7 for this type of data is statistically significant.

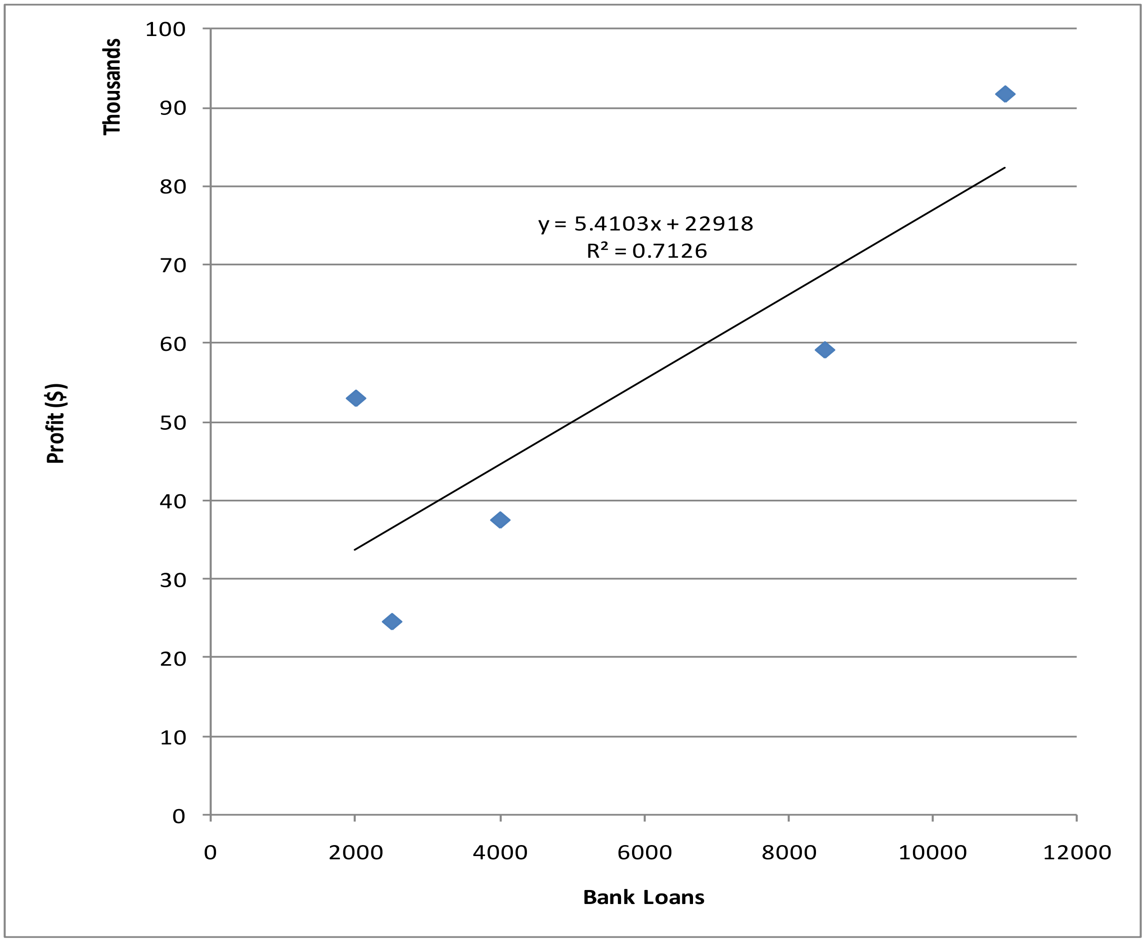

Figure 16 Loan Plotted Against Profit Data

Table 15 presents the bid efficiency data. Nichols (2010) considered that bid efficiency should be an indicator of success. The results do not support that view. There is no observed relationship in the data.

Table 15
Bid Efficiency

Rank	*Participant*	*No. of Bids*	*Jobs Won*	*Bid efficiency (%)*
1	5	218	17	8.7
2	3	92	22	23.91
3	4	167	13	8.8
4	1	147	16	10.88
5	2	70	8	13.88

DESCRIPTIVE STATISTICS OF THE WON JOB DATA

Table 16 lists the profit efficiency for each bidder. The only obvious correlation in this data is the link between the greatest profit and the highest profit efficiency. This subject is worth additional study, although no real conclusion can be drawn from this limited data set.

Table 16
Profit Efficiency

Rank	*Participant*	*Profit Efficiency ($)*
1	5	5,392.50
2	3	2,689.50
3	4	4,078.00
4	1	2,347.00
5	2	3,081.25

Figure 17 shows the percentage of jobs won in descending rank order. No conclusions can be reached from this data.

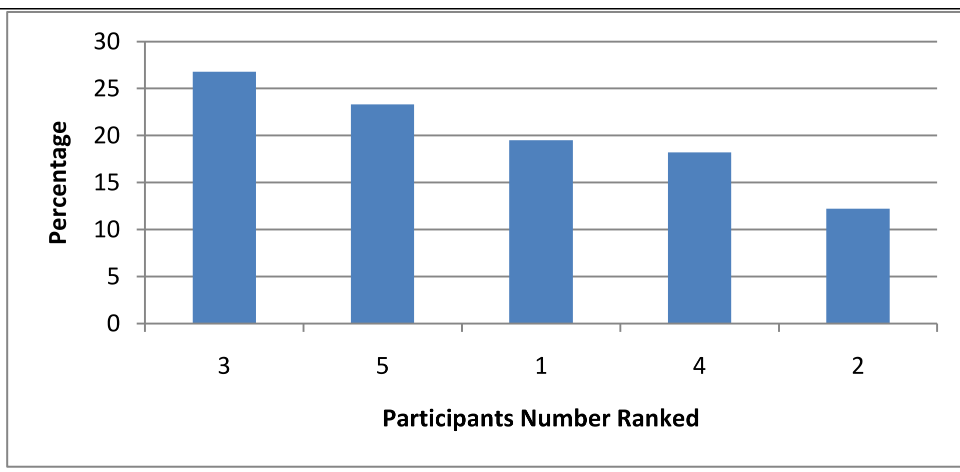

Figure 17 Overall Percentage Wins by All the Participants

The profit percentage of each of the participants has been plotted in the following figures, Figure 18 to Figure 22. The results show a broad scatter that suggests a more random process in winning jobs than the descriptive data listed above would suggest.

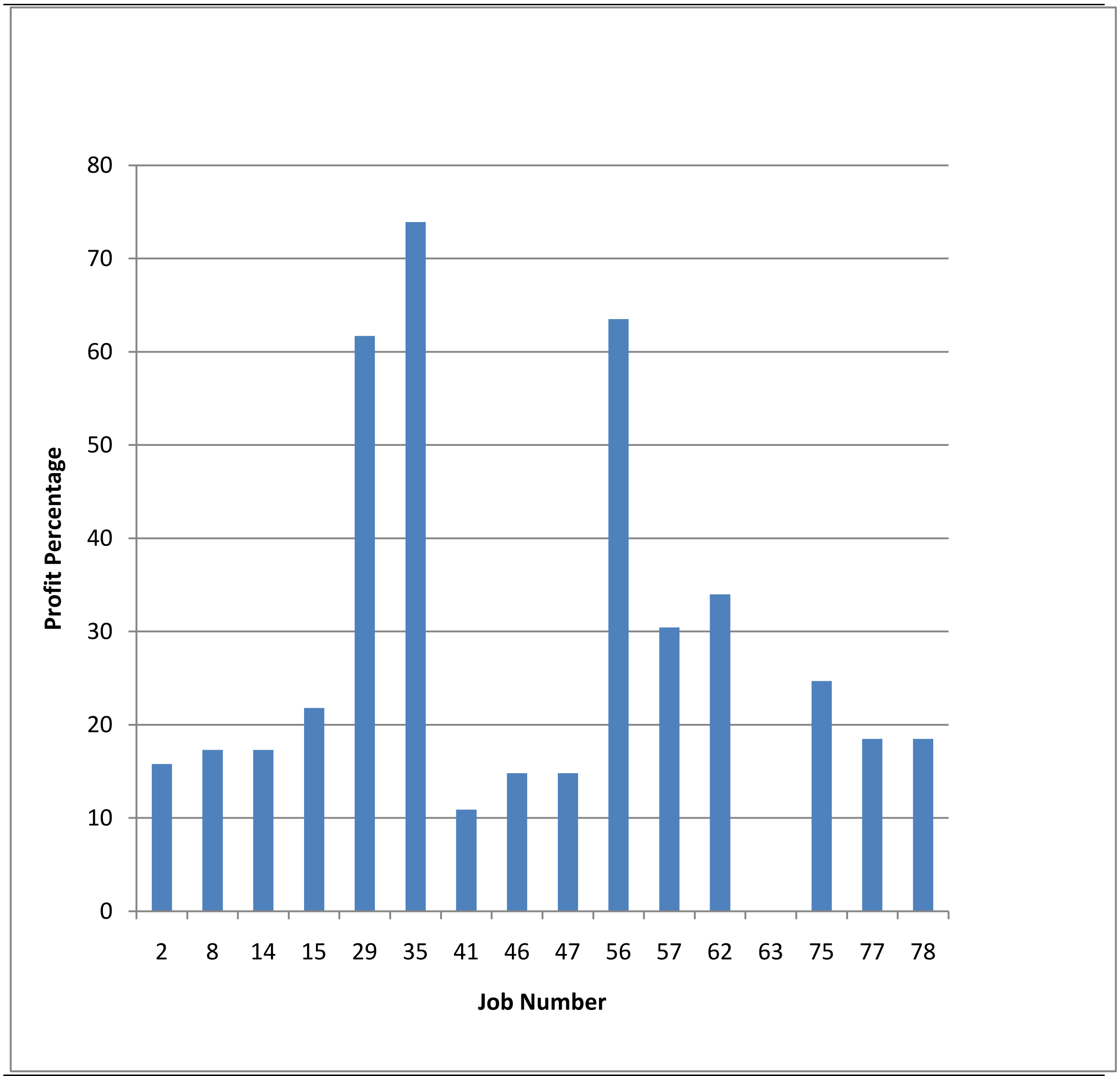

Figure 18 Participant One Histogram of Profit Percentage for Jobs

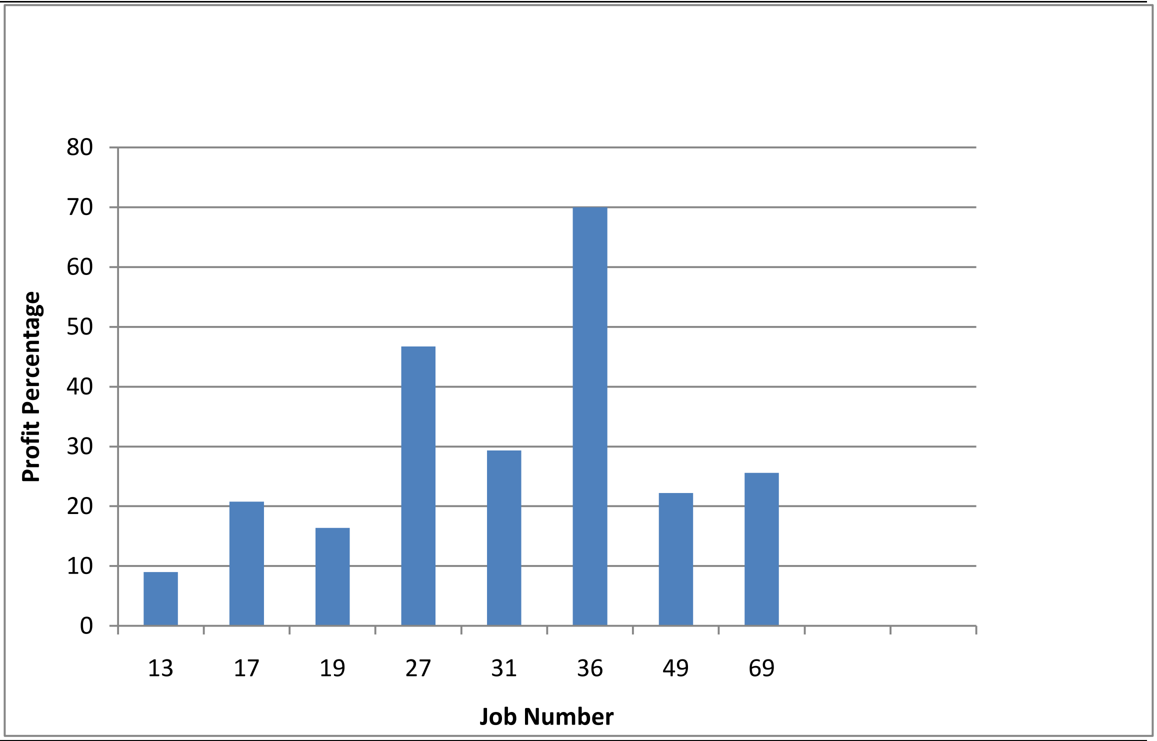

Figure 19 Participant Two Histogram of Profit Percentage for Jobs

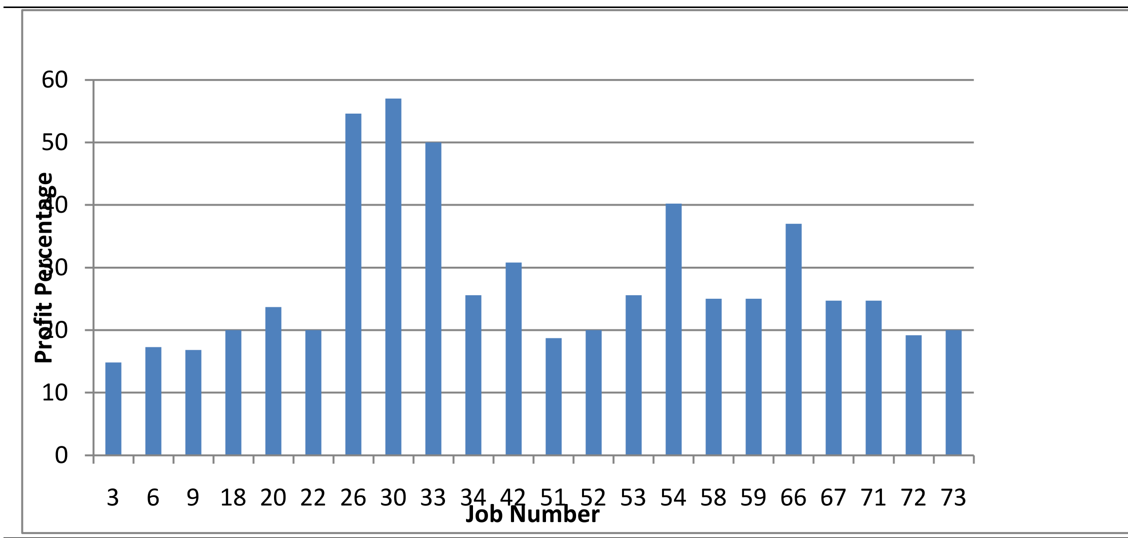

Figure 20 Participant Three Histogram of Profit Percentage for Jobs

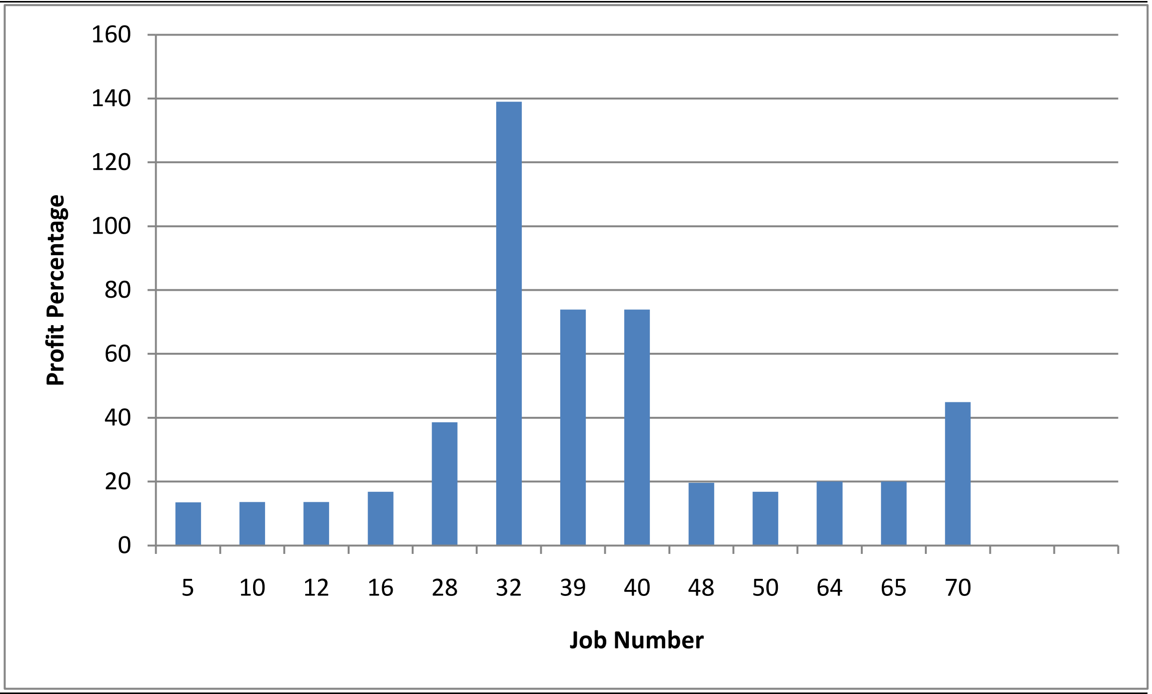

Figure 21 Participant Four Histogram of Profit Percentage for Jobs

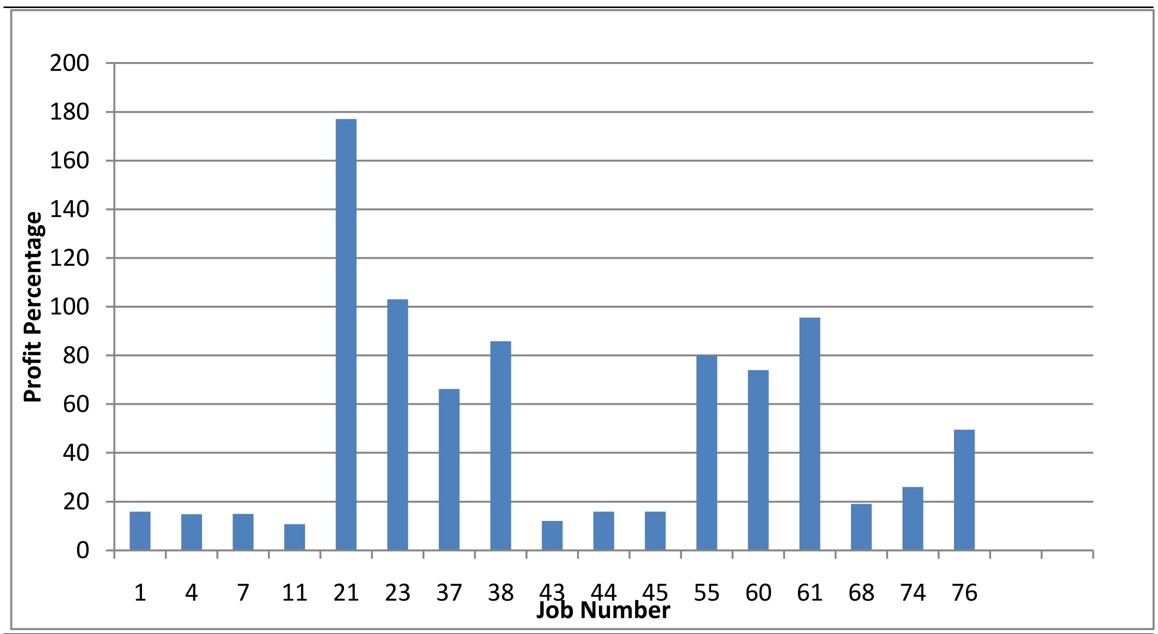

Figure 22 Participant Five Histogram of Profit Percentage for Jobs

Even participant five showed a significant variation in profit percentages.

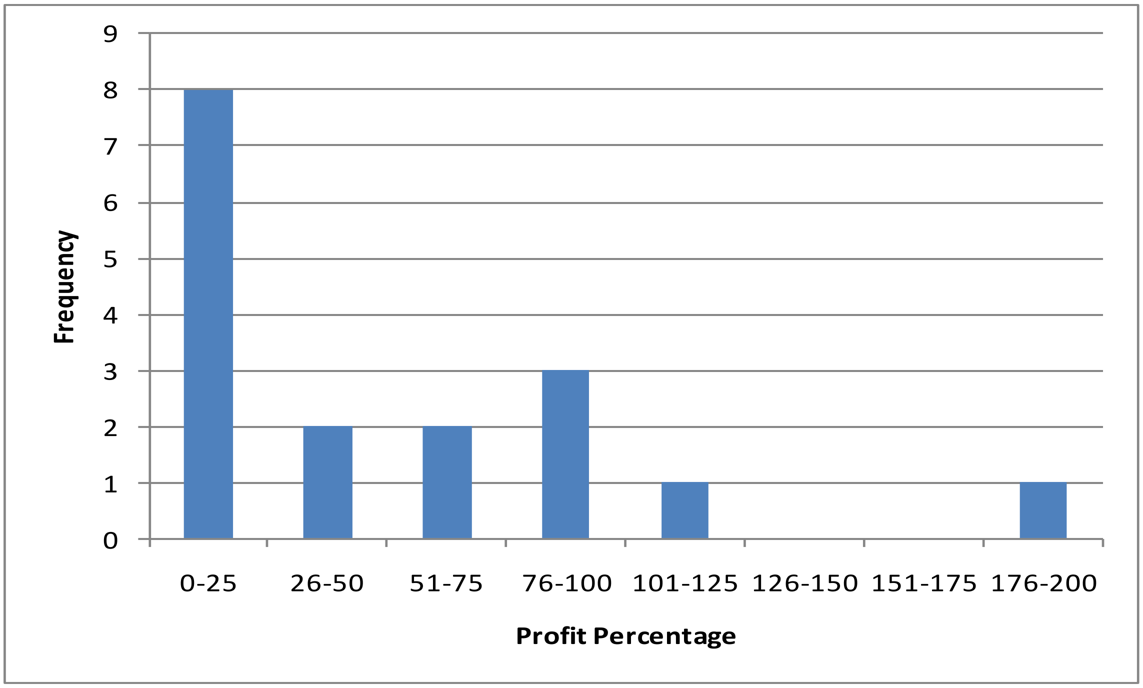

Figure 23 Histogram of Profit Percentages of Participant Five

The results show one extremely high percent profit, which may simply be a fortuitous event. But, Nichols (2010) suggested that the evidence points to high profits being achieved occasionally but randomly.

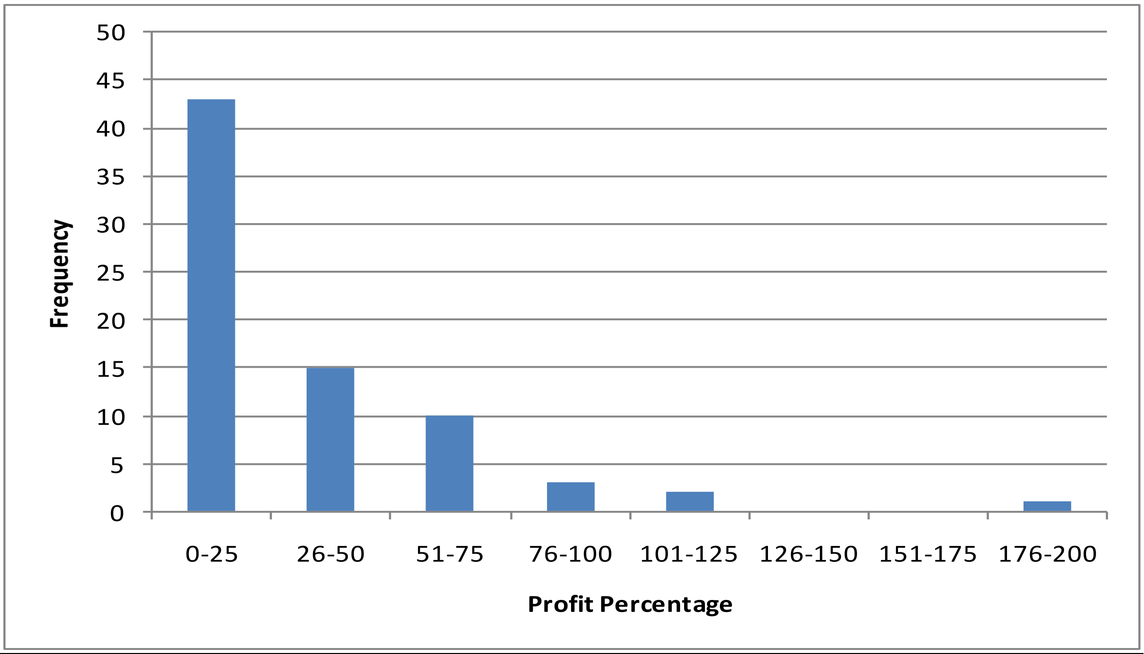

Figure 24 Histogram of all Participant Profit Percentages.

BID PERIOD COMPARISON

The bidding pattern with time for each participant is listed in Table 17 to Table 21. The results show the trend towards late bidding by some participants.

Table 17
Bids Made in 15-Minute Time Intervals - Participant 1

	Bid Periods							
Time (mins)	*7:00-7:15*	*7:20-7:35*	*7:40-7:55*	*8:00-8:15*	*8:20-8:35*	*8:40-8:55*	*9:00-9:15*	*total bids*
1	0	0	0	2	2	0	0	4
2	3	2	1	1	1	3	0	11
3	2	2	1	0	0	1	2	8
4	2	0	0	0	0	1	3	6
5	2	0	0	1	0	3	4	10
6	2	1	0	0	0	3	0	6
7	0	1	1	0	3	0	0	5
8	2	1	1	0	3	1	0	8
9	2	0	1	3	2	0	0	8
10	3	0	1	1	0	0	0	5
11	4	0	2	1	3	0	0	10
12	5	0	2	0	0	5	0	12
13	3	0	2	1	1	2	0	9
14	2	2	2	1	3	1	3	14
15	3	5	3	5	1	8	3	28

Table 18
Bids Made in 15-Minute Time Intervals - Participant 2

	Bids Periods							
Time (mins)	*7:00-7:15*	*7:20-7:35*	*7:40-7:55*	*8:00-8:15*	*8:20-8:35*	*8:40-8:55*	*9:00-9:15*	*total bids*
1	0	0	1	0	1	0	2	4
2	2	1	0	1	2	3	2	11
3	1	1	0	1	0	0	0	3
4	0	1	0	0	0	1	1	3
5	0	0	0	0	1	0	2	3
6	0	1	0	0	0	0	1	2
7	1	0	0	0	0	1	0	2
8	0	1	0	0	1	0	0	2
9	1	1	0	0	0	0	0	2
10	0	1	0	1	1	0	0	3
11	0	0	1	0	2	0	2	5
12	0	0	0	0	2	0	1	3
13	0	2	0	0	1	0	0	3
14	1	1	0	0	1	2	1	6
15	3	3	1	1	3	3	6	20

Table 19
Bids Made in 15-Minute Time Intervals - Participant 3

	Bid Periods							
Time (mins)	*7:00-7:15*	*7:20-7:35*	*7:40-7:55*	*8:00-8:15*	*8:20-8:35*	*8:40-8:55*	*9:00-9:15*	*total bids*
1	0	1	0	2	0	0	0	3
2	4	0	1	0	0	0	0	5
3	0	0	0	0	1	0	0	1
4	2	0	1	0	1	0	1	5
5	0	0	0	0	0	0	1	1
6	0	0	0	0	0	0	0	0
7	1	1	0	1	0	1	0	4
8	2	2	0	0	1	1	0	6
9	3	1	0	0	1	0	0	5
10	4	1	1	0	0	0	0	6
11	2	0	0	0	0	0	0	2
12	5	1	0	1	0	1	0	8
13	3	1	0	0	2	1	0	7
14	4	1	1	1	4	0	1	12
15	5	3	3	4	6	2	4	27

Table 20
Bids Made in 15-Minute Time Intervals - Participant 4

	Bid Periods							
Time (mins)	*7:00-7:15*	*7:20-7:35*	*7:40-7:55*	*8:00-8:15*	*8:20-8:35*	*8:40-8:55*	*9:00-9:15*	*total bids*
1	2	0	3	0	1	2	1	9
2	2	1	0	1	0	0	3	7
3	2	1	0	0	0	0	1	4
4	2	0	0	0	0	1	2	5
5	1	2	1	0	0	2	5	11
6	2	1	0	0	0	2	1	6
7	1	1	0	0	2	2	2	8
8	0	1	0	0	1	1	2	5
9	3	4	2	0	2	1	1	13
10	2	0	0	2	2	2	0	8
11	2	4	0	2	4	0	0	12
12	1	3	1	2	1	2	0	10
13	2	3	2	3	1	4	2	17
14	2	3	2	2	4	5	5	23
15	4	5	2	4	3	5	7	30

Table 21
Bids Made in 15-Minute Time Intervals - Participant 5

				Bid Periods				
Time (mins)	*7:00-7:15*	*7:20-7:35*	*7:40-7:55*	*8:00-8:15*	*8:20-8:35*	*8:40-8:55*	*9:00-9:15*	*total bids*
1	2	0	3	0	3	0	0	8
2	1	0	2	0	1	4	1	9
3	1	0	1	0	1	0	2	5
4	1	1	0	2	0	1	1	6
5	0	1	0	1	0	0	2	4
6	1	0	0	0	1	2	3	7
7	2	2	1	1	5	1	2	14
8	2	1	0	2	6	0	2	13
9	0	3	0	0	3	5	1	12
10	2	1	1	3	4	0	1	12
11	1	6	1	3	4	0	1	16
12	2	3	2	3	3	4	1	18
13	2	4	3	4	4	6	2	25
14	3	5	4	5	4	5	5	31
15	2	5	4	5	6	7	6	35

Figure 25 shows the bid period data for Participant 1. This participant bids at a tolerably constant rate, showing the usual flurry of bids in the last two minutes. This bidder ranked fourth in profit.

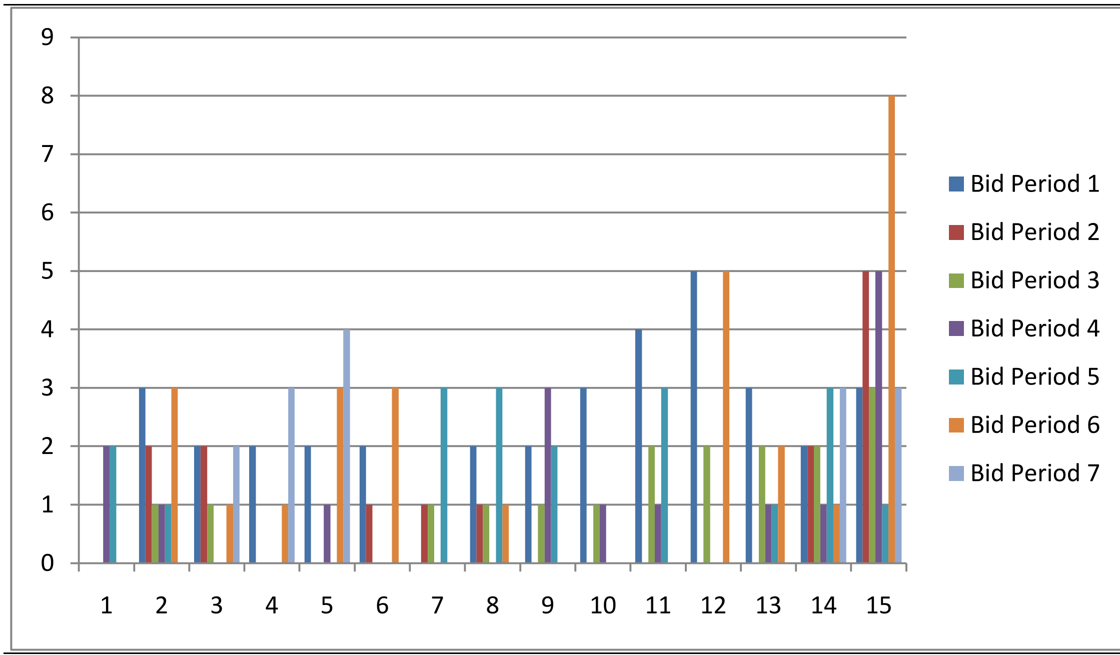

Figure 25 Participant 1: Bid Distribution per Minute

Figure 26 shows the bid period data for Participant 2. This participant bids at a tolerably constant, but low rate, showing the usual flurry of bids in the last two minutes. This bidder ranked fifth in profit. The bidder is a poor performer.

Figure 27 shows the bid period data for Participant 3. This participant bids at a usually low rate, showing the usual flurry of bids in the last two minutes. This bidder ranked second in profit. The bidder is a selective performer.

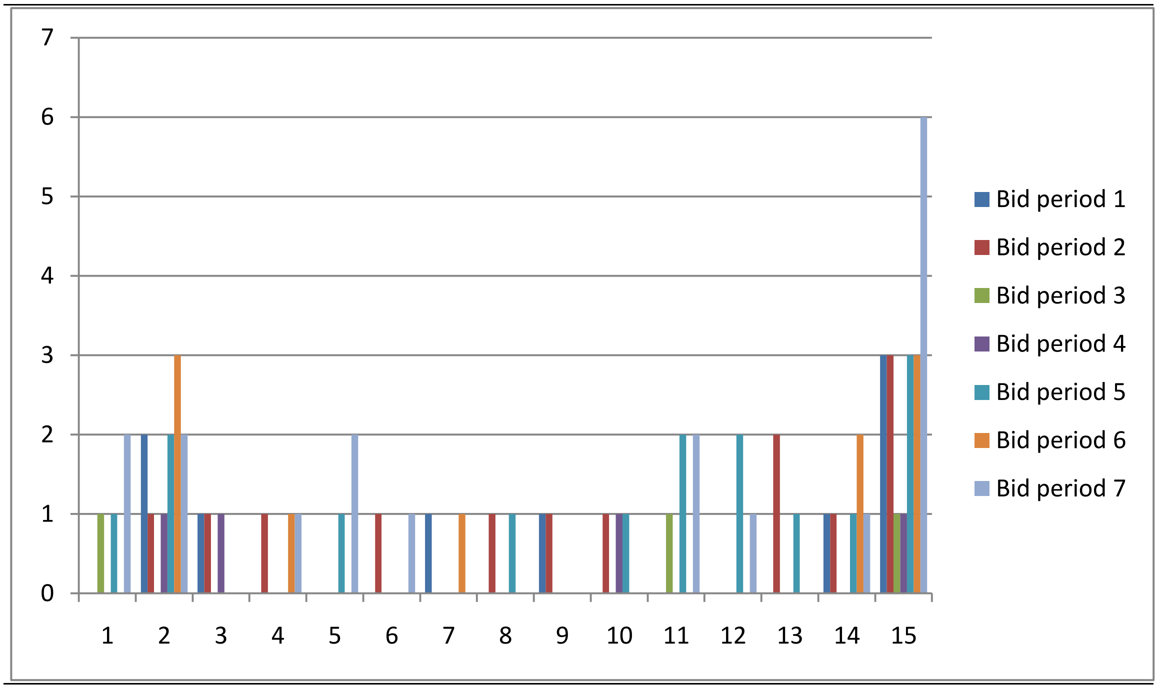

Figure 26 Participant 2: Bid Distribution per Minute

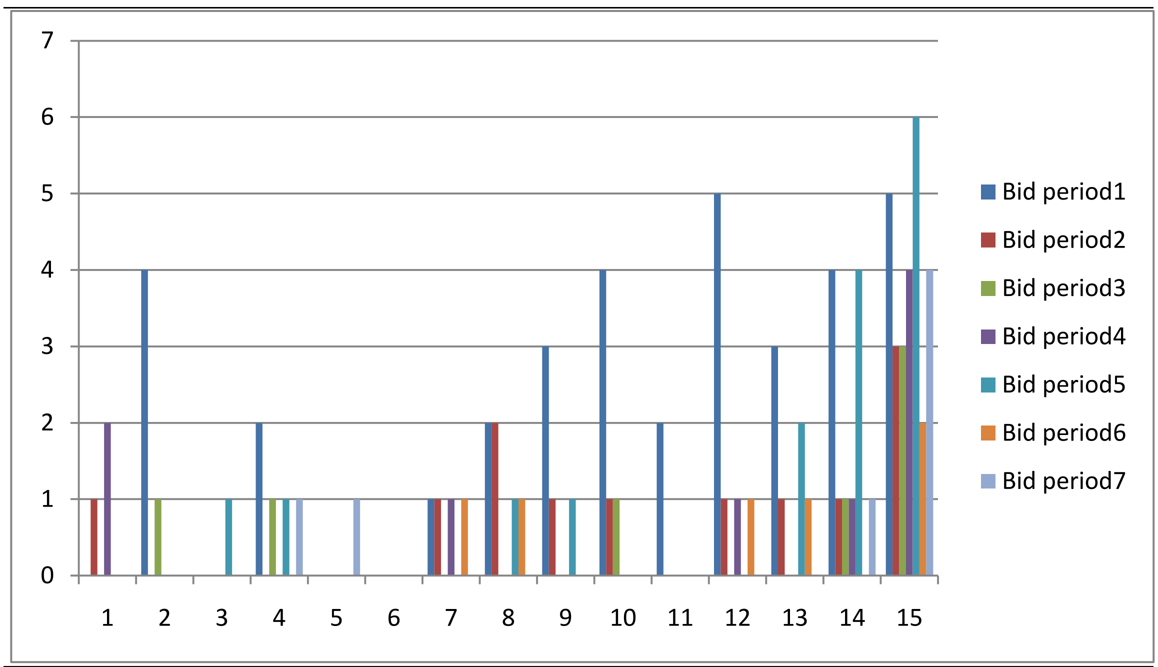

Figure 27 Participant 3: Bid Distribution per Minute

Figure 28 shows the bid period data for Participant 4. This participant bids at a constant low rate, showing the usual flurry of bids in the last two minutes. This bidder ranked third in profit. The bidder is best described as a non-selective performer.

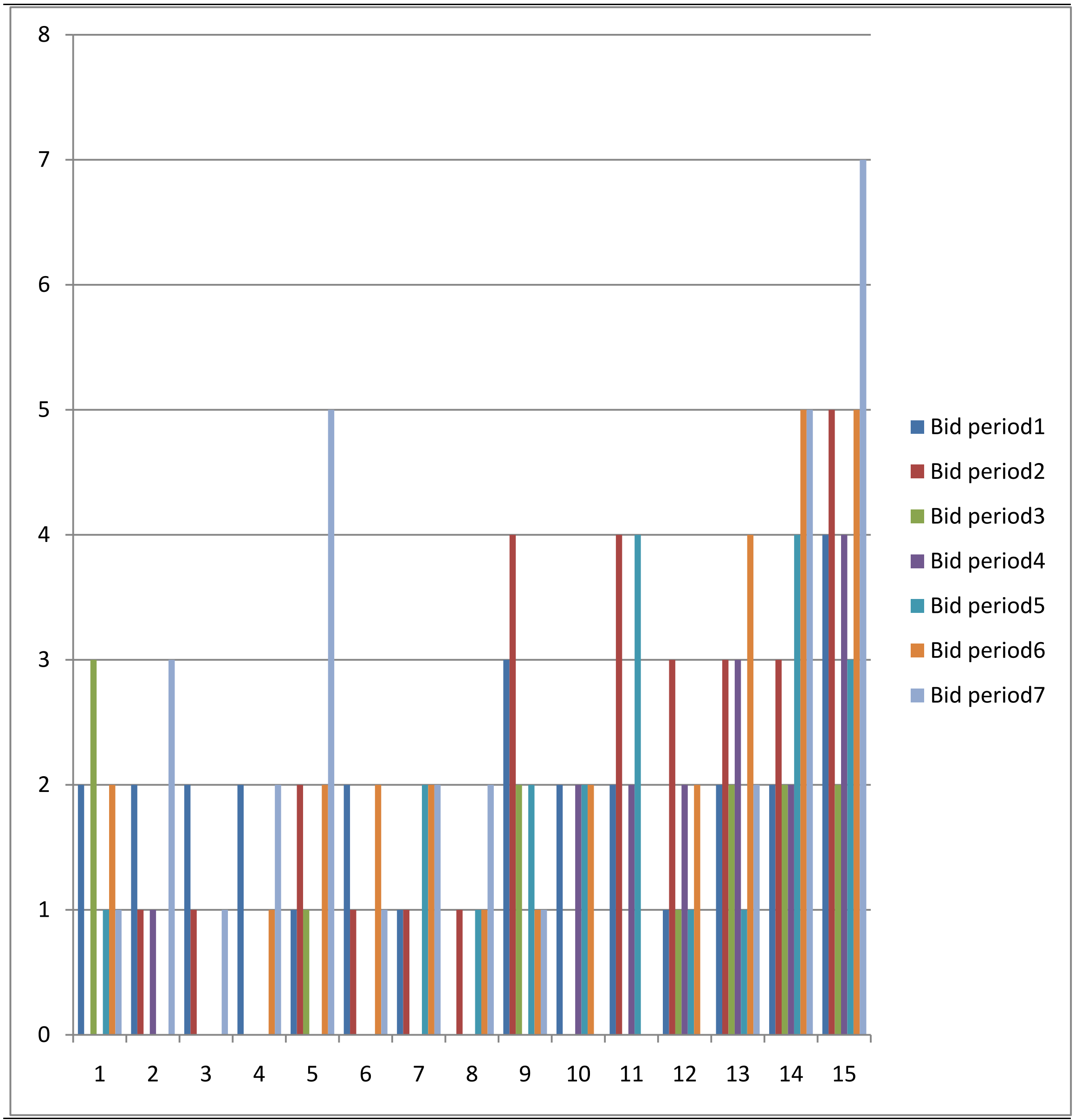

Figure 28 Participant 4: Bid Distribution per Minute

Figure 29 shows the bid period data for Participant 5.

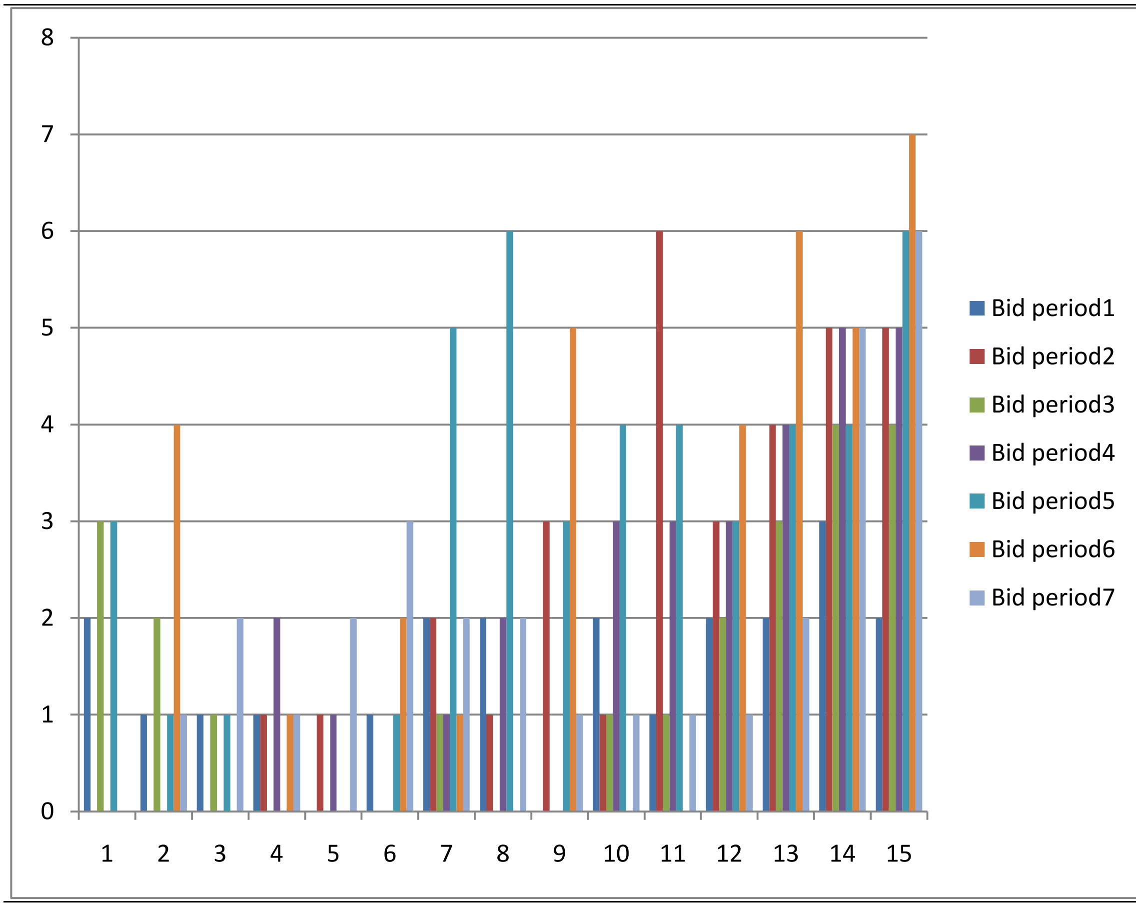

Figure 29 Participant 5: Bid Distribution per Minute

This participant bids at a slowly increasing rate, showing the usual flurry of bids in the last five minutes. This bidder ranked first in profit. The bidder is best described as a highly selective performer.

From the above histograms, it is evident that participant 3, with the greatest number of jobs, adopted the strategy of bidding late. This participant did most bidding in the last 3 minutes and won more jobs when compared to participant 5, with the maximum profit and bid number, who bid aggressively right from the start.

The Table 22 below shows the total number of bids in each minute for all bidders.

Table 22
Bids Made in 15-Minute Time Intervals - All Participants

	Bid Periods							
Time (mins)	*7:00-7:15*	*7:20-7:35*	*7:40-7:55*	*8:00-8:15*	*8:20-8:35*	*8:40-8:55*	*9:00-9:15*	*total bids*
1	4	1	7	4	7	2	3	28
2	12	4	4	3	4	10	6	43
3	6	4	2	1	2	1	5	21
4	7	2	1	2	1	4	8	25
5	3	3	1	2	1	5	14	29
6	5	3	0	0	1	7	5	21
7	5	5	2	2	10	5	4	33
8	6	6	1	2	12	3	4	34
9	9	9	3	3	8	6	3	41
10	11	3	3	7	7	2	1	34
11	9	10	4	6	13	0	3	45
12	13	7	5	6	6	12	2	51
13	10	10	7	8	9	13	4	61
14	12	12	9	9	16	13	15	86
15	17	21	13	19	19	25	26	140

Figure 30 shows that the participants bid at a slowly increasing rate, with the usual flurry of bids in the last five minutes. This pattern is observed in nearly all the participants' individual histograms.

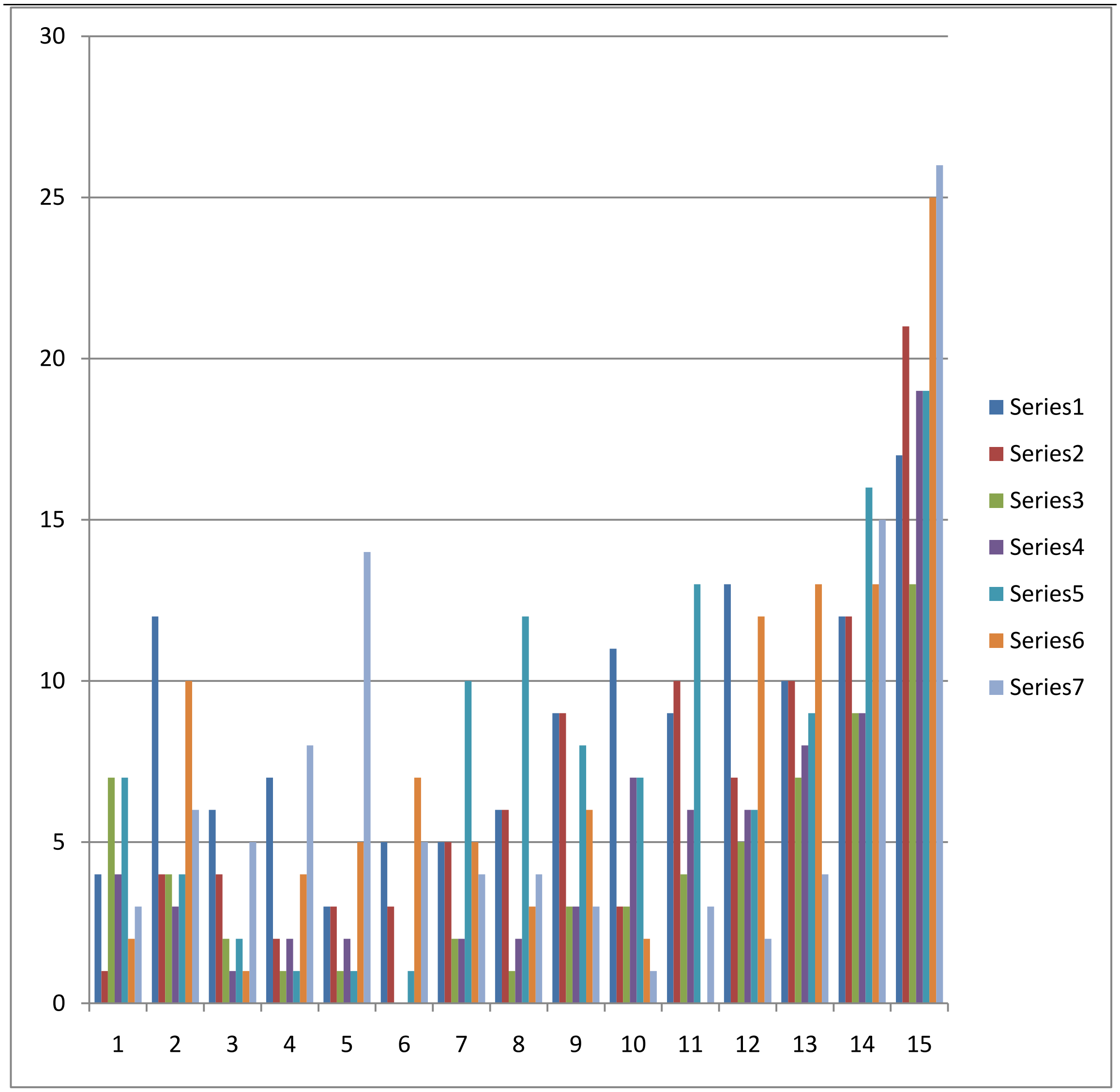

Figure 30 All Participants: Bid Distribution per Minute

Rogers (2010) suggested a stock chart plot for the aggregated data. Table 23 shows the highest, lowest and the average bids of each minute of the game.

Table 23

Highest, Lowest and Average Number of Bids in Each Minute

Minutes -	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
high	9	11	8	6	11	7	14	13	13	12	16	18	25	31	35
low	3	5	1	3	1	0	2	2	2	3	2	3	3	6	20
Average	4.8	7.5	4	5	5.6	4.5	6.6	7	8.2	7.3	9.3	10.5	12.3	16.6	25.8

Figure 31 shows a stock plot, which gives the highest, lowest and the average number of bids that were made during each minute (all 15 bidding periods).

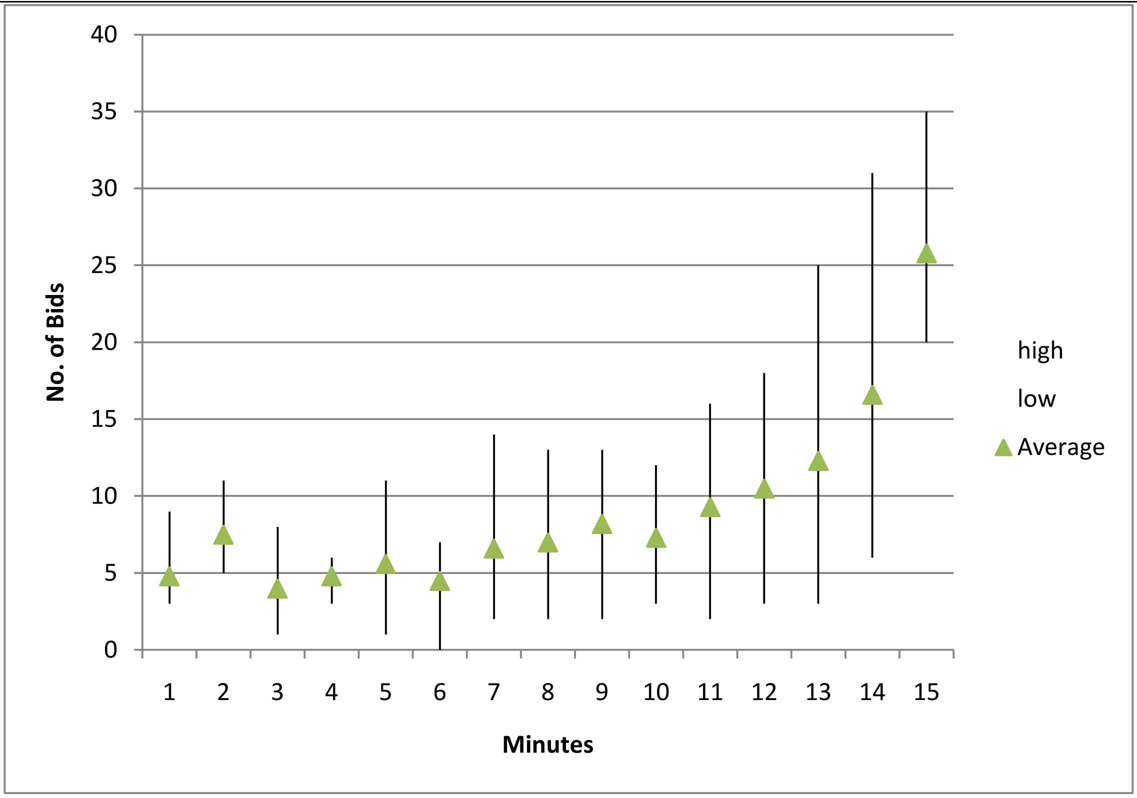

Figure 31 Figure Showing Highest, Lowest, and Average Number of Bids in Each Minute.

The curve made by average bids is an approximate smooth curve, but the lowest and the highest bid points are not as apparently smooth as the average curve. Figure 32 shows a plot of the count of the average bids per minute for the 15 minutes game.

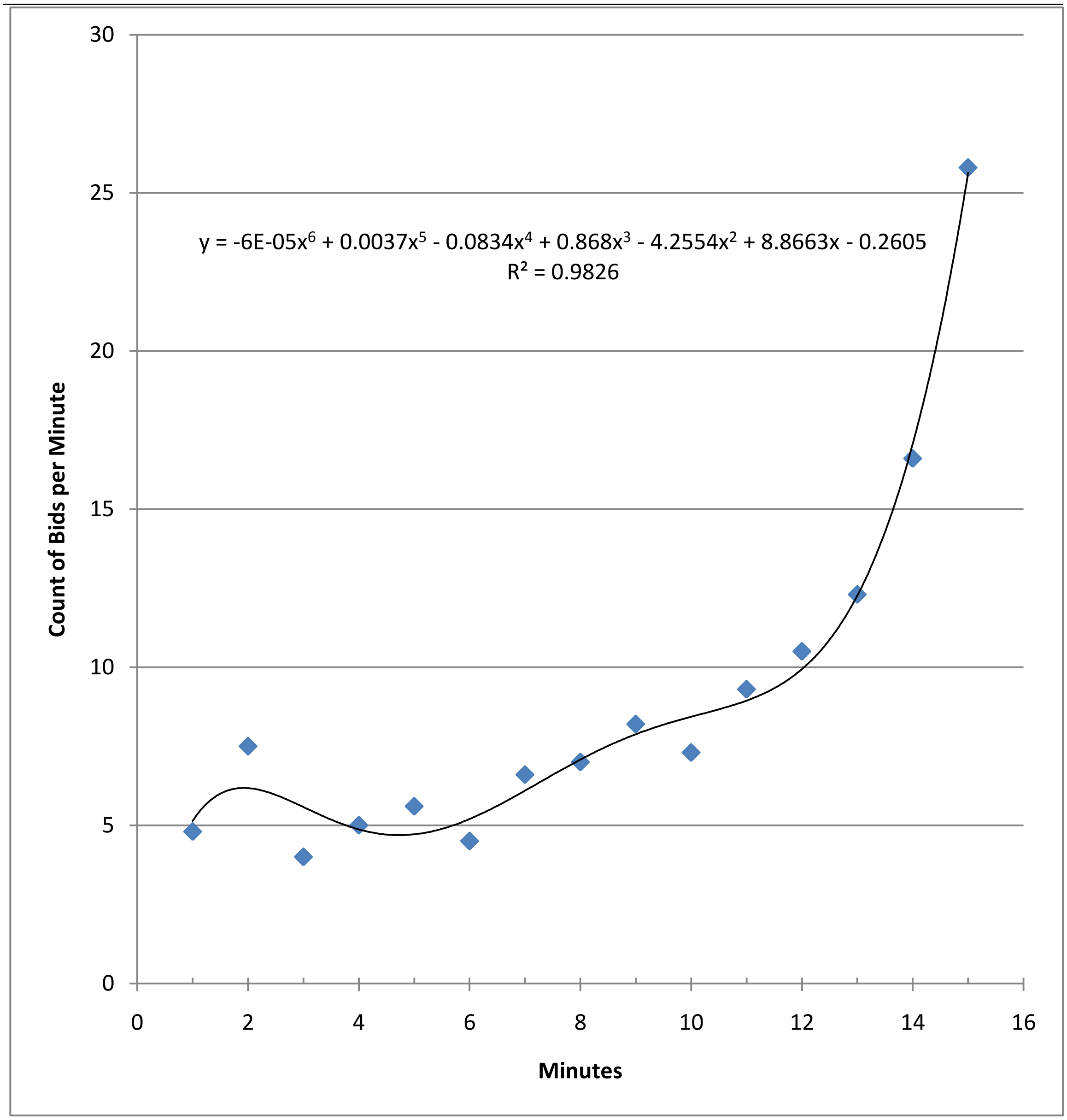

Figure 32 Histogram showing Average bids per Minute to the Jobs Won

A significant amount of time has been spent analyzing the data to review the results from the alternatives. The first step is to analyze and to plot the bid distribution for all participants per minute, as shown in Figure 30, followed by a determination of the average results per bid minute as shown in Figure 31.

Figure 30 showed that a pattern existed in the bidding data, with an average increase with bids per minute across the game time. Figure 32 shows a simple statistical analysis, where a sixth order polynomial is fitted to the data. The result has a regression co-efficient of 0.98; whilst the fit is good, the cyclic movement of the data about the fitted line is evident. The accepted analysis technique for this type of data is to determine the difference between the trend line and the data points to create a residuals data set, followed by a Fast Fourier transform analysis of the residuals (Kordzakhia, 1998).

An alternative to the approach above was to take the logarithms of the count data, to reduce the residuals from the higher minutes, when compared to the earlier minutes. Figure 33 shows the logarithm of the graph of bids per minute, with a second order equation fitted to the data.

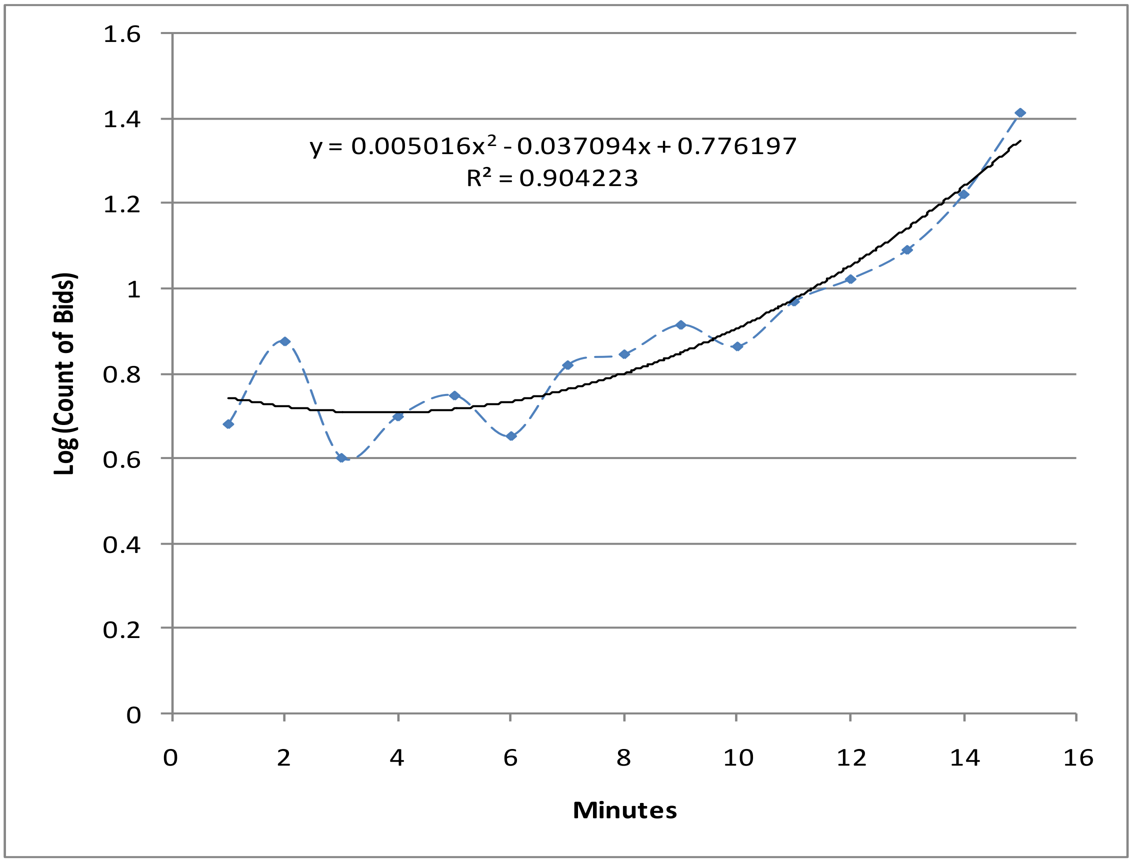

Figure 33 Logarithm of Bids per Minute

The residuals show a cyclic trend that can be analyzed using the Fast Fourier transforms. There are 15 data points that can be mapped to a 16 array for a Fast Fourier transform analysis (Brigham, 1988). Figure 34 shows the Fast Fourier transform plotted against period in place of the usual frequency x axis plot.

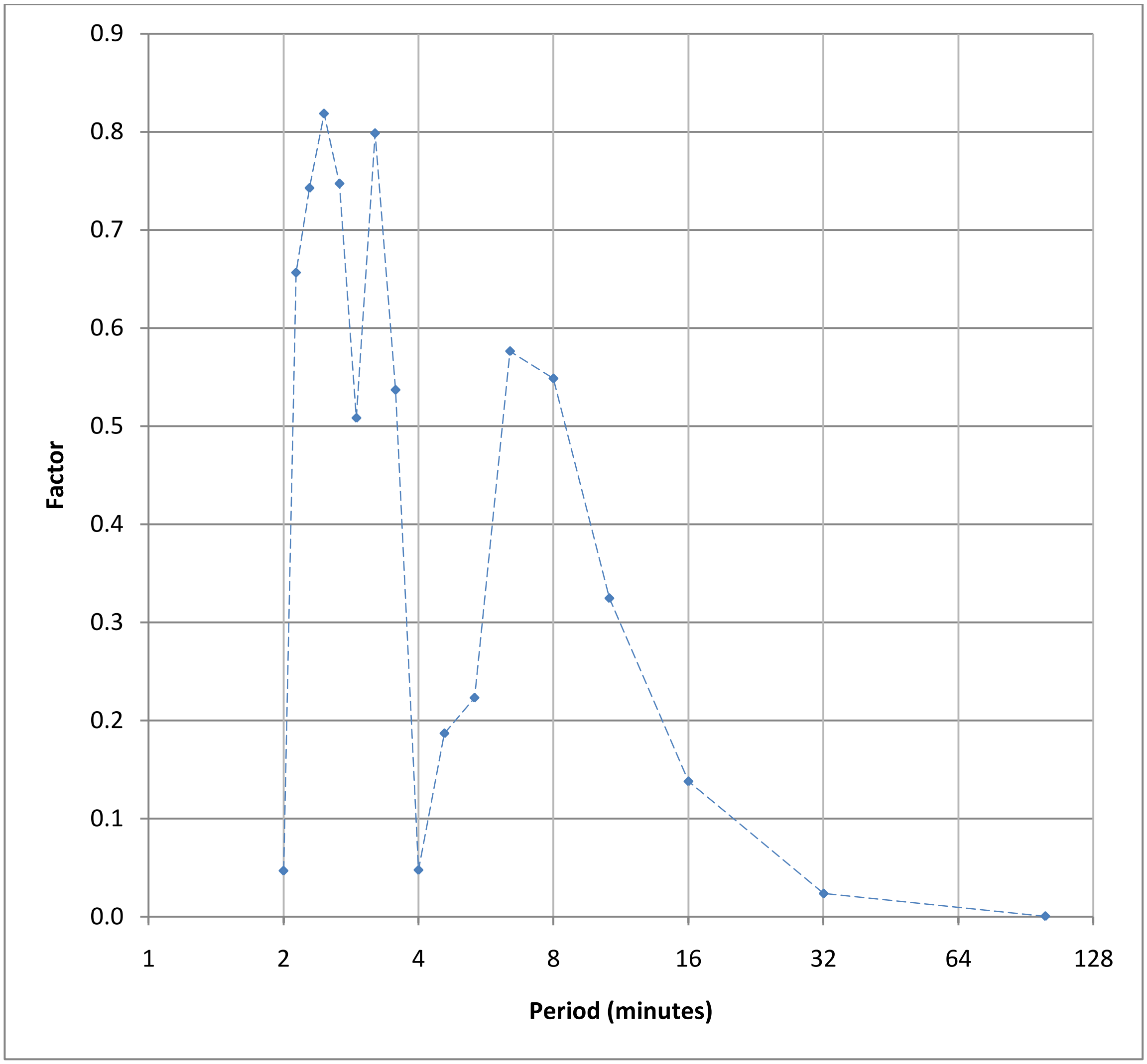

Figure 34 Fast Fourier Transform Results Plotted Against Period

The results in this figure show two sinusoidal patterns in the data, one with a period of about 3 minutes and the other with a period of approximately 7.5 minutes. The results show a sinusoidal pattern in the bidding with a cycle of three minutes, which suggests the bidders are following a pattern, which suggests further research. Whilst the second pattern has a period of about 8 minutes represents the rate of change in bidding to some extent. It is not unusual for statistical data relate to human to show this type of pattern. Figure 35 shows a plot histogram of total number of bids made participant 2 per minute. A third order polynomial has been fitted to the point data.

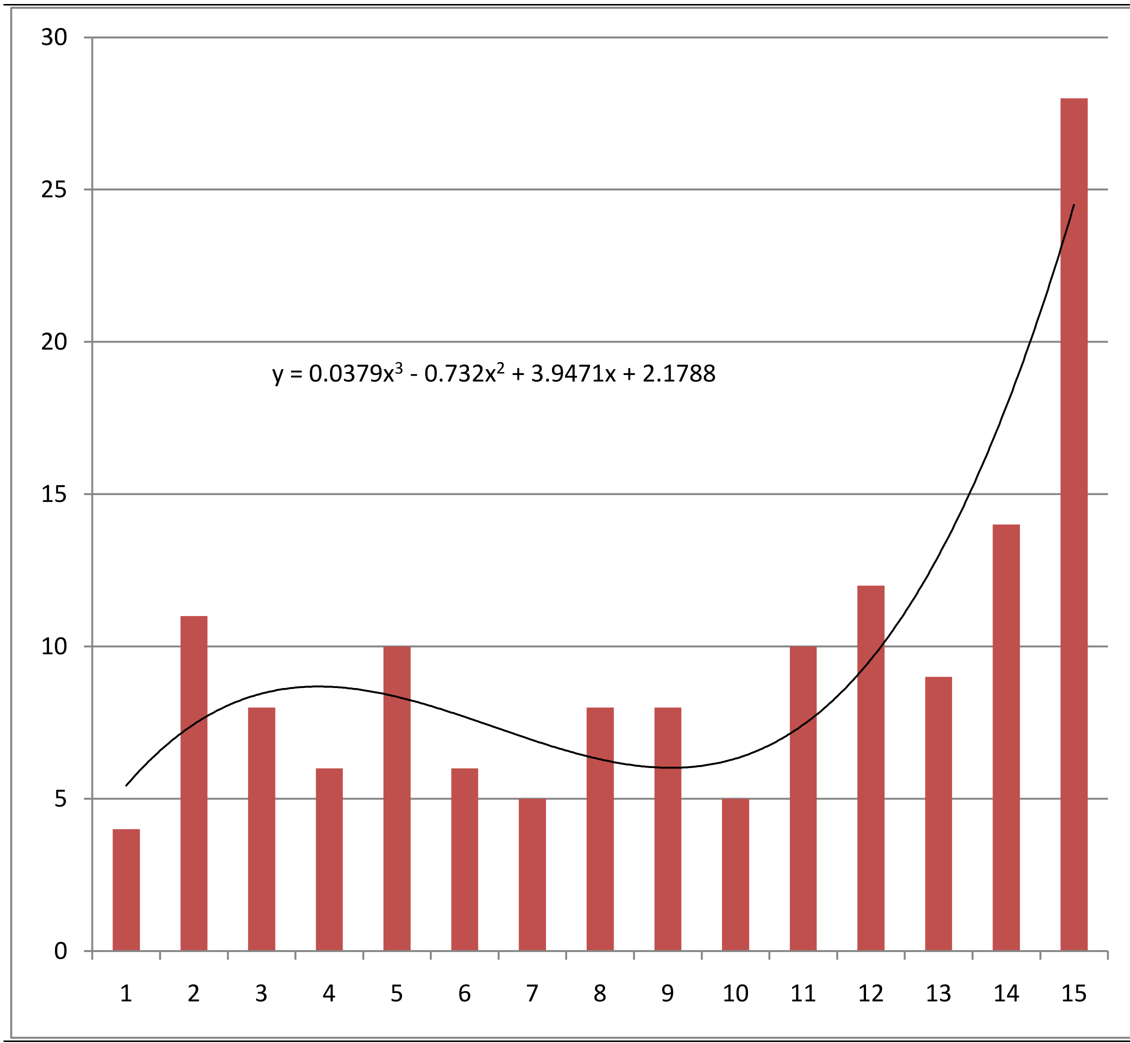

Figure 35 Participant 1: Total Bid Distribution per Minute

Participant 1 bids at a tolerably constant rate until minute 14 and then doubles the rate of bidding. Participant 1 had the second lowest profit.

Figure 36 shows a plot histogram of total number of bids made Participant 2 per minute. A third order polynomial has been fitted to the point data.

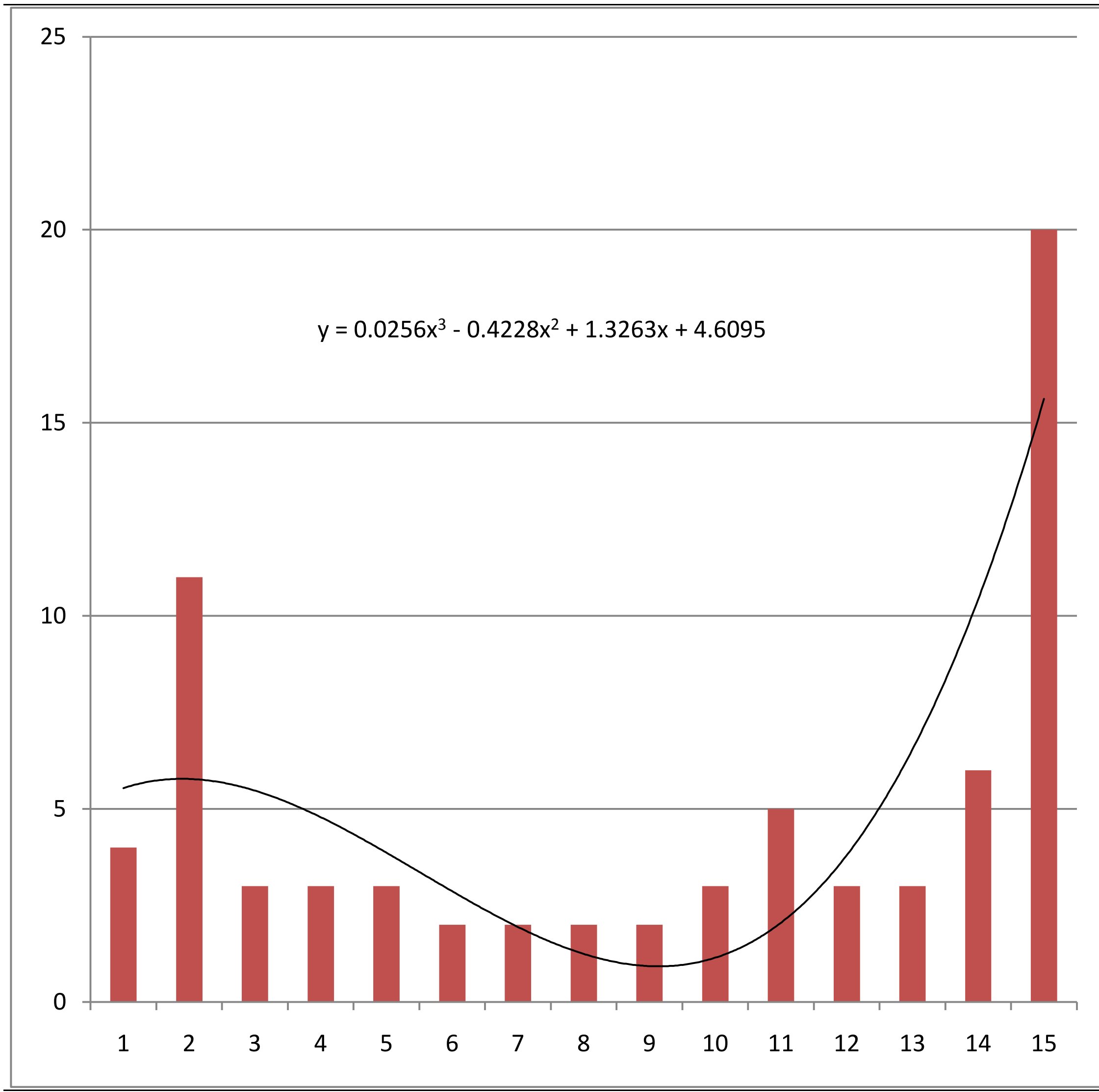

Figure 36 Participant 2: Total Bid Distribution per Minute

Participant 2 bids aggressively in the last minute, but bid at a low rate for the bulk of the duration of the game. An aggressive increase in the second minute and the final minute.

Figure 37 shows a plot histogram of total number of bids made participant 3 per minute. A third order polynomial has been fitted to the point data.

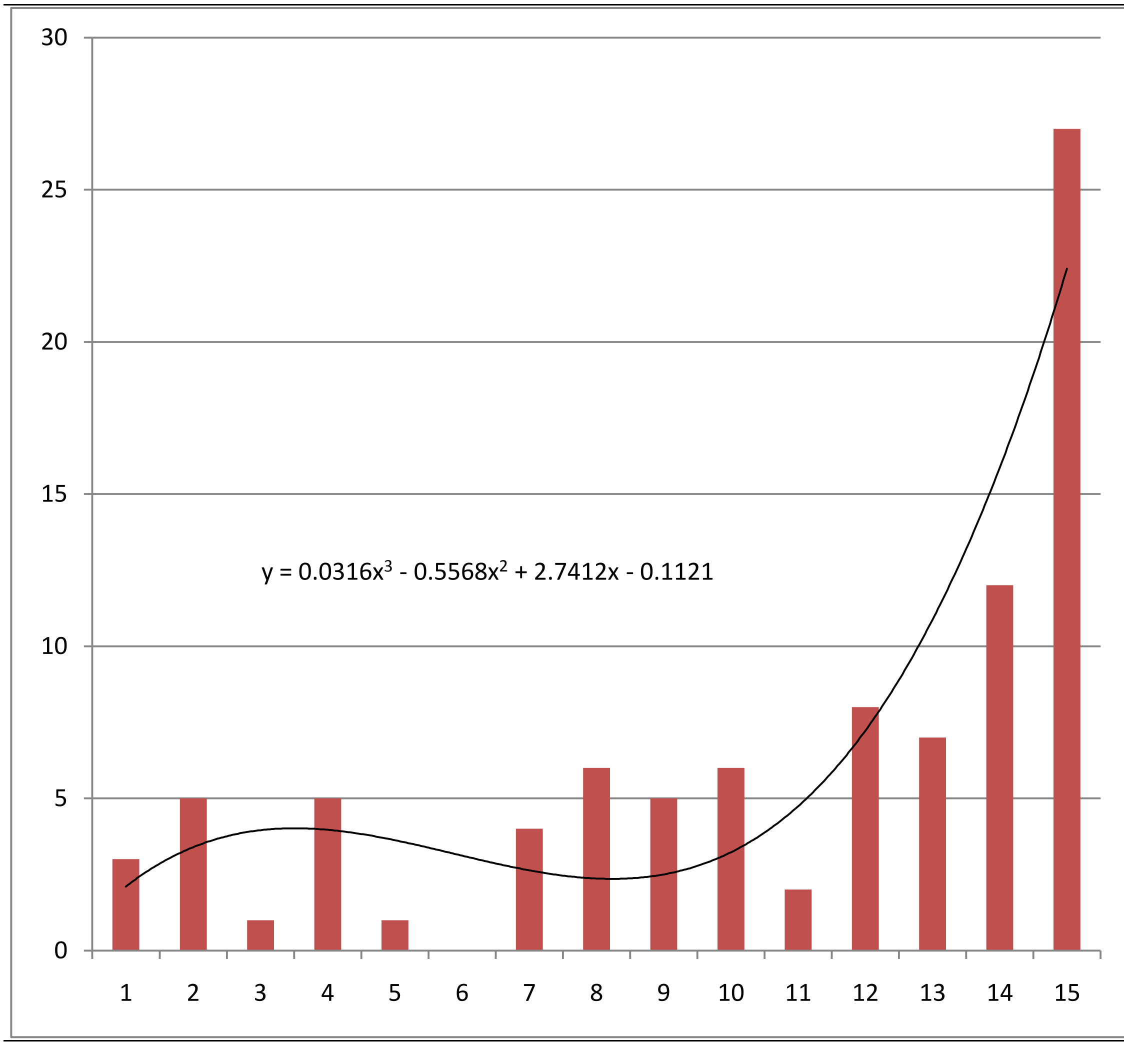

Figure 37 Participant 3: Total Bid Distribution per Minute

Participant 3 bids aggressively in the last minute, but as the second highest profit taker, the pattern for Participant 3 is highly variable.

Figure 38 shows a plot histogram of total number of bids made participant 4 per minute. A third order polynomial has been fitted to the point data.

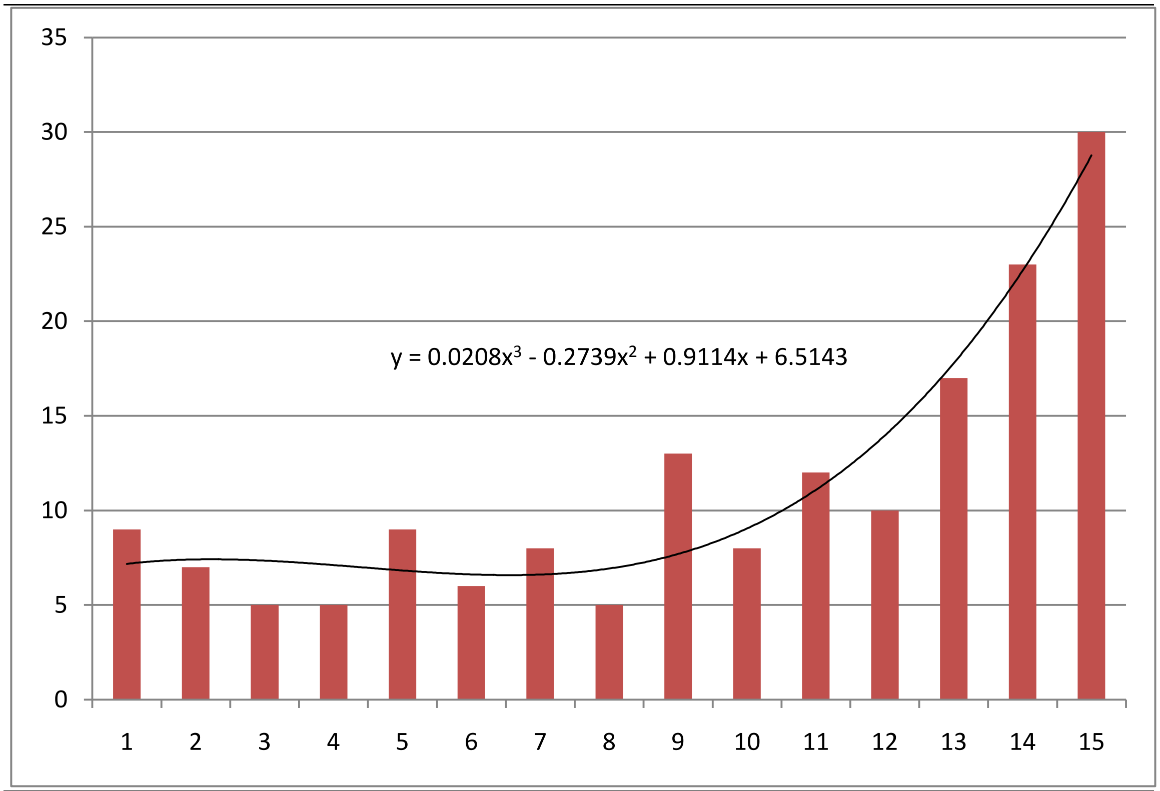

Figure 38 Participant 4: Total Bid Distribution per Minute

Participant 4 bids aggressively throughout the game when compared to the others, but performed in the middle of the pack in terms of profit.

Figure 39 shows a plot histogram of total number of bids made participant 5 per minute. A third order polynomial has been fitted to the point data.

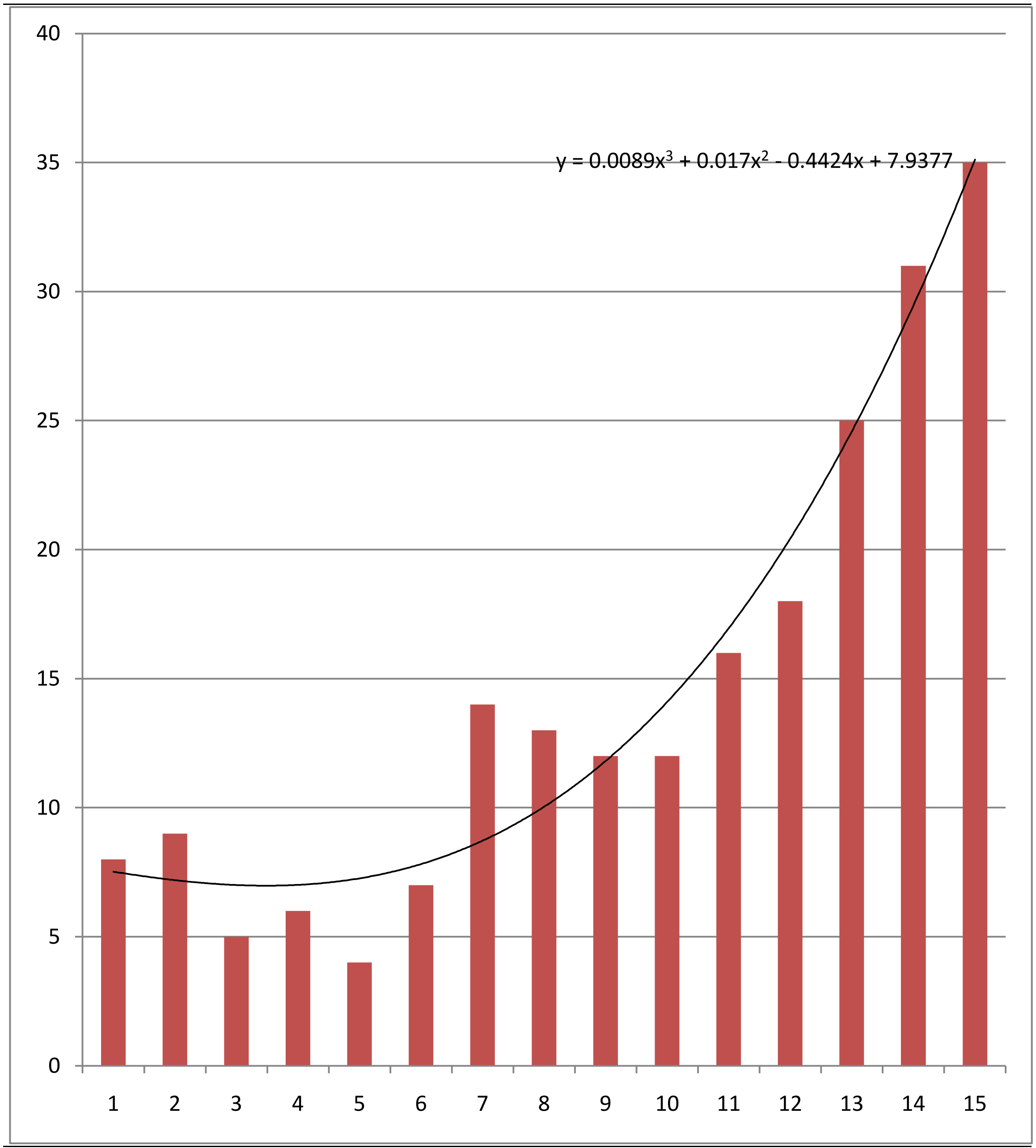

Figure 39 Participant 5: Total Bid Distribution per Minute

Participant 5 bids aggressively from the seventh minute and has the maximum profit for the game. Table 24 shows the coefficients for the third order fitted equation for the five participants.

Table 24
Third Order Equation Coefficients

Participant	*Profit ranking*	*Constant*	*X*	*X^2*	*X^3*	*Comment*
1	4	2.1788	3.947	0.732	0.0379	Constant
2	5	4.6095	1.3263	0.4228	0.0256	Low rate, aggressive at minute 2 and 15
3	2	0.1121	2.7412	0.5568	0.0316	Variable
4	3	6.5143	0.9114	0.2739	0.0208	Aggressive
5	1	7.9377	0.4424	0.017	0.0089	Aggressive late

This table provides data for establishing an algorithm for an electronic bidder. There are no visible trends in plots of the coefficients against the profit ranking, from plotting all of the coefficients against the profit ranking.

DIFFERENTIAL BID DATA

One of the critical numbers of interest in analysis for bidding in any system is the difference between the winning bid and the second last bid on each job. Table 25 to Table 29 present the difference in the second to winning bid in dollar terms for the five participants. There is a significant amount of information in the bid count data. This is an area of future research.

Table 25
Difference between the Winning Bid and the Second Last Bid on Each Job that Participant 1 Won

Job ID	*Difference between the winning bid and the second last bid*
2	99
8	1
14	200
15	50
29	500
35	1999
41	1000
46	1999
47	900
56	500
57	500
62	11000
63	12000
75	1000
77	145
78	145

Table 26
Difference between the Winning Bid and the Second Last Bid on Each Job that Participant 2 Won

Job ID	Difference between the winning bid and the second last bid
13	100
17	200
19	68100
27	14300
31	76775
36	3000
49	1000
69	750

Table 27
Difference between the Winning Bid and the Second Last Bid on Each Job that Participant 3 Won

Job ID	*Difference between the winning bid and the second last bid*
3	1
6	1
9	1
18	-
20	67350
22	188000
26	4000
30	5000
33	3000
34	4000
42	3000
51	100
52	500
53	1
54	3500
58	7500
59	2500
66	1000
67	2500
71	6500
72	7099

Table 28
Difference between the Winning Bid and the Second Last Bid on Each Job that Participant 4 Won

Job ID	*Difference between winning bid and the second last bid*
5	250
10	299
12	25
16	300
28	15000
32	14000
39	2000
40	2000
48	500
50	500
64	1999
65	5500
70	5000

Table 29
Difference between the Winning Bid and the Second Last Bid on each Job that Participant 5 Won

Job ID	*Difference between the winning bid and the second last bid*
1	149
4	999
7	150
11	650
21	1000
23	1000
37	2000
38	1000
43	500
44	500
45	800
55	500
60	1000
61	5000
68	100
74	1
76	1

Table 30 lists the participants in profit ranking order and summarizes the lost money for each participant in terms of mean and standard deviation.

Table 30
Money Lost Descriptive Statistics

Profit Ranking	*Participant*	*Average of Lost Money* *$*	*Standard Deviation of Lost Money* *$*
1	5	903	1,172
2	3	15,277	43,201
3	4	3,644	5,134
4	1	2,002	3,764
5	2	20,528	32,460

Clearly, participant 5 is a more disciplined bidder than the rest of the bidders. The data does not follow a Gaussian distribution. Table 30 shows the money lost by the bidders while making the final bid on the job won. The results show a great variation in number but it can be clearly seen that the average money lost by participant 5 is much lower when compared to other participants. Participant 5 did not win the maximum number of jobs, but yet this participant obtained the maximum profit out of all 5 participants.

Figure 40 shows a graph of average number of bids to the jobs won by the bidders. There appears to be a weak but somewhat direct relationship in this data that can be used in an analysis. The data provides bounds for establishing the behavior of an electronic bidder that may be used in future games.

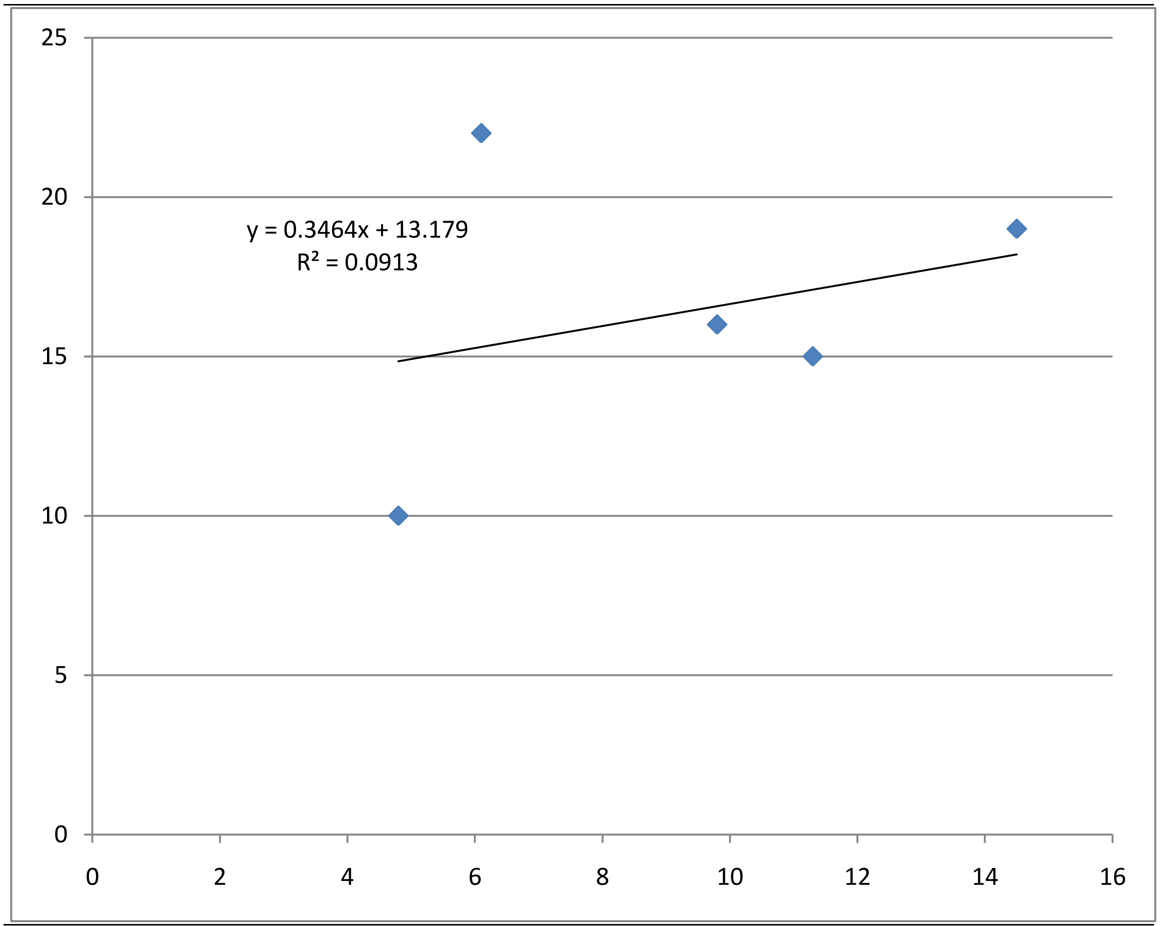

Figure 40 Histogram of Average Number of Bids to Jobs Won

Figure 41 shows a graph of average number of bids to the profit made by the bidders. There appears to be a weak but somewhat direct relationship in this data that can be used in an analysis. The data provides bounds for establishing the behavior of an electronic bidder that may be used in future games.

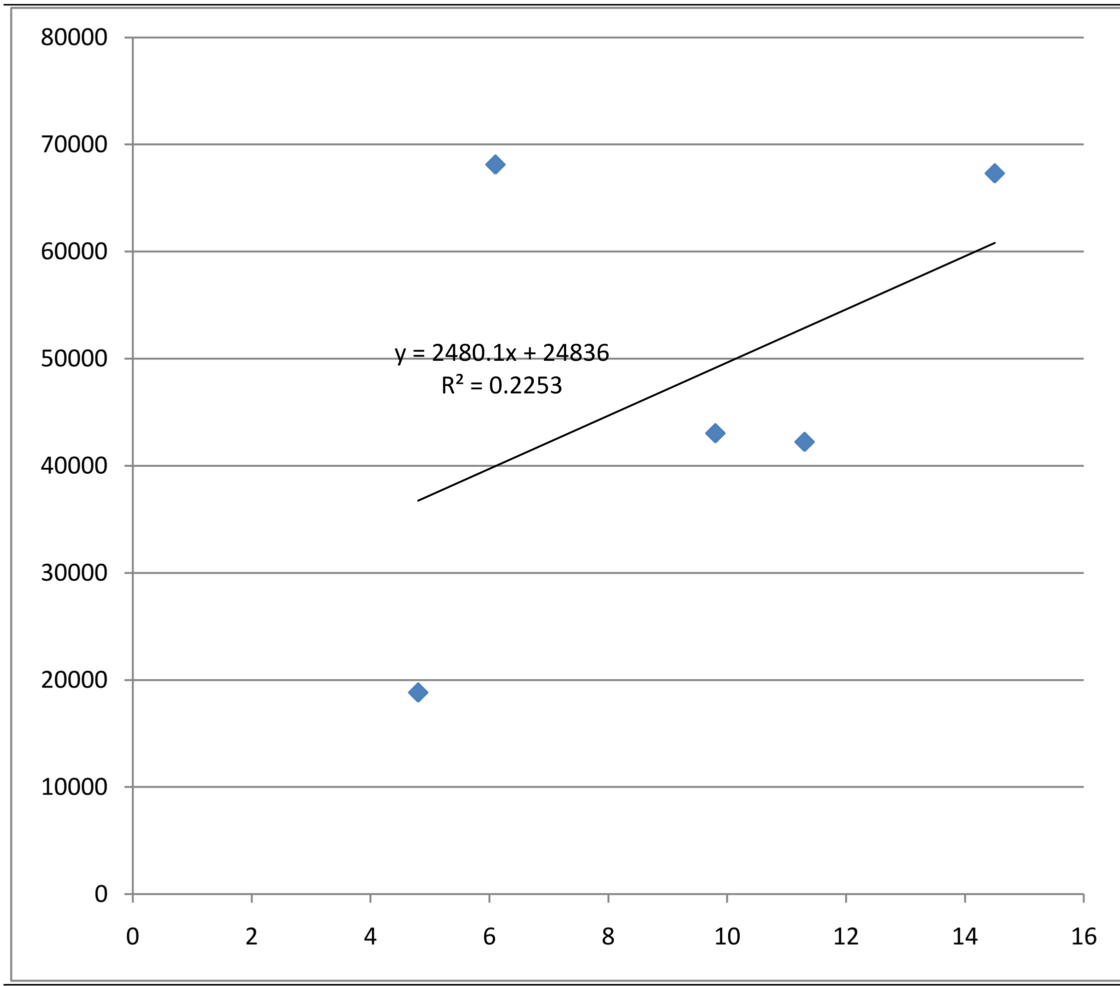

Figure 41 Histogram of Average Number of Bids to Amount of Profit Made by Each Participant

CHAPTER V

ANALYSIS OF THE RESULTS

The research objectives for this study are:

1. Establish plots of the bidding data,
2. Compare the bidding patterns shown in the plots with time for all bidders,
3. Determine if evidence exists in the bidding data to confirm the existence of the ω game and does it represent some form of collusion, and
4. Compare the returns of the different bidders in the α game to determine if there are differences in bidding returns and does it represent some form of collusion.

As noted in the literature review, this type of study can become data rich but analysis poor, because of the quantity of the data and the limited ability to determine patterns and trends in such a large quantity of data. Significant advances have been made in the field of data mining (Chakrabarti, 2009), but the data collected by van Vleet is not amenable to these techniques.

This chapter presents a summary of the bidding data, bidding patterns, and comments on the game ω and game α to provide the results that address the objectives.

BIDDING DATA

Objective One was to establish plots for the bidding data. The job distribution per week is based on a roll of three dice, which because of the truncated integer nature of the 216 possible combinations results in a slightly non-Gaussian distribution as shown in Figure 11 (pg. 34). This study lasted for seven game weeks and covered 76 jobs, for which 692 bids were made by the five participants. Table 7 presents the descriptive statistics for the number of jobs per week. The mean of 10.875 is slightly higher than the distribution mean and the standard deviation of the job data per week is 76% of the standard deviation for the dice distribution.

Figure 12 shows the profits for the 76 jobs. The profit data was normalized using equation (1). A histogram summary of the normalized profit levels is presented in Table 8. This histogram is the key to understand the driving economic mechanism for game α. This game is created by the purchaser in deciding to use the RAB system and represents the basis for the tacit collusion observation by van Vleet (2004). The tacit collusion is observation of the cannier participants obtaining a higher return relative to the average returns.

BIDDING PATTERNS

Chouhan (2009) postulated that four trend periods were observable in the job price data with contract number. A Student's t Test analysis showed that Chouhan's data could be described in these terms. A similar analysis of van Vleet's data, shown in Table 11, supports the concept of trends in data, but the results are not as conclusive as Chouhan's. This is an area for future research.

A number of results from this analysis deserve additional research. The first result is the observation of a positive correlation between the bank loans used the profit returned as shown in Figure 16 (pg. 49).

The maximum profit returned was to Participant 5 who earned 91,673 or about 3.7 times as much as Participant 2 who was lowest with 24,650. Participant 5 had the lowest total for the amount between this participant's bid and the bid being replaced in the game. This is a critical point for maintaining higher profit levels. The histogram of the profit percentages shown in Figure 24 shows a reasonable distribution form, although data from other studies will be required to confirm the pattern. This pattern however provides one of the driving mechanisms for the α game. There are differences in the returns of bidders, which is the first observation of the interaction between the ω game and the α game.

GAME ω

There is significant construction community resistance to using Reverse Auction Bidding in the construction industry. The purchaser or υ player is clearly trying with this method to minimize the average costs of the components or goods purchased from the λ player. The υ player collectively has to accept the bids if they are made within the rules, and so in game terms the average cost of the jobs is the measure of success of the Reverse Auction Bidding system used by the υ player.

The υ player creates the game and has to accept the economic consequences of this decision. van Vleet (2004) used the term tacit collusion to describe the behaviour of the λ player, who did not offer a uniform job price structure. This is the behaviour causing concern for the industry participants. Nichols (2010) postulated the presence of the α game within the overall Reverse Auction Bidding game.

The game ω is in essence a one to one game between the set of players (λ_i player) and the purchaser, but the α game is a multiplayer game and hence less amenable to exact modelling.

υ player is trying to exert economic pressure on the λ player, with the clear goal of reducing the average cost of jobs. There is no evidence in van Vleet's data that the υ player succeeds in implementing this strategy and a brief review of the α game suggests the converse may be true in some situations, specifically considering the significant returns obtained by participant 5.

GAME α

λ_i players are attempting to maximize their returns from the game. The results show that some players in this game can attain higher returns than the competitors. This observation has driven the Reverse Auction Bidding research at TAMU since van Vleet's study, as attempts are made to research this game and understand the driving mechanisms.

The game is created by the υ player, which has been amended in subsequent case studies to introduce some constraints on bidding limits (Chouhan, 2009). Analysis of van Vleet's case study data suggests that four factors influence the α game and hence the distribution of returns to the λ_i players. These factors are:

1. A λ_i player makes a bid offer, and two things can occur:
    a. The bid will remain for the duration of the game and be accepted
    b. The bid will be undercut
2. The subsequent bids by different λ_i players can be:
    a. offered at the limit of the game money, which in this case is technically one dollar.

b. offered at an amount higher than the limit of the game money, so that for example on job 63 the differential was $12,000

3. The player λ_i offers a bid less than the amount of the job to that participant.

4. Time runs out in some form of control on the duration of the game

In terms of Factor 1a, this strategy offers the λ player the greatest return in the ω game and the greatest cost to the υ player. This form of game play has been discussed anecdotally when Nichols (2010) has talked to bidders involved in real Reverse Auction Bidding systems. The strategy for maximizing the return in terms of this play is to offer the highest amount the υ player will tolerate without ending the game; the υ player is clearly the loser in this strategy.

In terms of Factor 1b, this strategy now becomes for a two-player game between the first bidder on the job and the second bidder. The best strategy for the second bidder is to offer the minimum reduction that will be accepted by the υ player, which in this game is one dollar. Table 30 illustrates how poorly this group of bidders grasped this economic fact. The data shown in Table 30 shows that fact 2b is used more than 2a, even though 2a is in the best economic interest of the bidders. It is suggested that this is a result of naive bidders. In terms of factor 3, a disciplined player in a steady state economic condition should not make this mistake. The game controls for this to some extent.

However, as Chouhan postulated the λ player learns with time how to increase the returns whilst remaining within the game rules. This observation is evident on Figure

12. One then conclude that Reverse Auction Bidding is not bid shopping and the λ player has many opportunities to make returns in excess of the minimum bid offered in the game. There is insufficient data to determine the controlling factors in the α game observed by van Vleet, but the initial observation of co-operation between the players can not be ignored in understanding Reverse Auction Bidding. The only comment offered is the υ player created the rules and must live with the economic consequences.

In terms of the research objectives;

1. Plots of the bidding data shows a pattern that has been observed in subsequent games.
2. A comparison has been made, the interest results are the increase in average total number of bids with time.
3. Clearly the ω game exists, otherwise the profit data would be a constant amount per bid at the lowest amount allowed by the rules. There is clearly a floor at about ten percent profit, but participants will take a higher profit when presented with the the opportunity, either because of fortuitous Factor 1a, event or in normal play with results in terms of factor 1b.
4. Participant 5 shows the greater returns. The game strategy for good players is a subject for future research.

CHAPTER VI

CONCLUSIONS

van Vleet (2004) commenced the long running study into Reverse Auction Bidding at TAMU. van Vleet developed an ASP and Microsoft Access based web system for accepting bids for a simple residential slab project in Houston. The purpose of this study was to review van Vleet's results in light of some of the subsequent case studies. The review has identified a two game system that offers some guidance as to the game play. For the RAB game, van Vleet created a game scenario. The projects were house slabs for a production homebuilder at six sites. Each bidder was started with a capacity for three jobs per week. The number of participants in this study was five, giving a nominal total capacity of fifteen jobs per week, although with the use of a bank guarantee the bidder could increase their job capacity. The case study covered a game period of seven weeks, with 612 bids and 76 jobs. The complete set of statistics on the jobs and bids is summarized in the Methodology and Results Chapters. The critical elements appear to be the two games played within the Reverse Auction Bidding game.

The first game has been designated the ω game, in reality a two player game between the purchaser and the set of bidders. The purchaser wins in this game by reducing the average cost of the jobs. The bidders win by increasing the average cost of the jobs. This game is an open transparent economic game, where the purchaser, designated the υ player, provides full economic disclosure on the bids during the game.

In stable economic conditions, this game creates the opportunity for higher returns to canny bidders.

The second game has been designated the α game, which is a multiplayer game between the bidders. The set of bidders are attempting to maximize their return in this game by gaining an economic advantage over the other bidders. This is normal economics of everyday business. However, the game play strategy, which is identified as being effectively controlled by three factors, provides an opportunity for increased returns for a canny player. It is assumed that the players are disciplined and will not under bid the job.

These factors are:

1. A λ_i player makes a bid offer, and two things can occur:
    a. The bid will remain for the duration of the game and be accepted
    b. The bid will be undercut
2. The subsequent bids by different λ_i players can be:
    a. offered at the limit of the game money, which in this case is technically one dollar.
    b. offered at an amount higher than the limit of the game money, so that on job 63 the differential was $12,000
3. time runs out in some form of control on the duration of the game

In conclusion, Reverse Auction Bidding systems are not bid shopping, but the tenet that the purchaser will reduce costs in this type of system compared to the traditional closed bid system is not confirmed with van Vleet's data and any careful consideration of the results of canny players in the α game suggests higher than average returns are made by some bidders. The critical observation is the number of bids that are covered by Factor 1a, which matches the anecdotal evidence of real Reverse Auction Bidding systems.

REFERENCES

Borowski, E. J., & Borwein, J. M. (1989). *Dictionary of mathematics* (Second ed.). Glasgow; Scotland: Collins.

Brigham, E. O. (1988). *The fast Fourier transform and its applications*. Englewood Cliffs; NJ: Prentice.

Chakrabarti, S. (2009). *Data mining*. Burlington; MA: Elsevier.

Chaudary, S. (2009). *Reverse Auction Bidding.* Unpublished M.S. Thesis, Texas A&M University, College Station.

Chouhan, M. (2009). *Bidders personality and its significance.* Unpublished Professional Paper, Texas A&M University, College Station.

Gregory, S. (2006). *Tacit collusion in Reverse Auction Bidding.* Unpublished Professional Paper, Texas A& M University, College Station.

Kim, Y. (2004). Reverse Auction Bid site web pages. College Station: Texas A&M Unviersity.

Kingsley-Hughes, A., Kingsley-Hughes, K., & Read, D. (2004). VBSCRIPT 2nd Edition. Indianapolis; IN: Wiley.

Kordzakhia, N. (personal communication to J.M. Nichols, 1998). *Fast Fourier transform analysis of statistical data*.

Little, W., Fowler, H. W., Coulson, J., Onions, C. T., & Friedrichsen, G. W. S. (1973). *The shorter Oxford English dictionary on historical principles*. Oxford; UK: Clarendon Press.

Nichols, J. M. (personal comminication to .Guhya, November 14, 2009). *Cost of doing business in the Consulting Industry*. College Station, TX

Nichols, J. M. (personal communication to D.Guhya, February 20, 2010). *Tacit collusion in Reverse Auction Bidding*. College Station, TX

Panchal, N. (2007). *Reverse Auction Bidding: Case study*. Unpublished professional paper at College Station: Texas A&M University.

Rogers, G. (personal communication to D.Guhya, March 10, 2010). *Analysis suggestions for Reverse Auction Bidding analysis*.

Shankar, A. (2005). *Reverse Auction Bidding: A Case Study*. Unpublished professional paper at College Station: Texas A&M University.

van Vleet, R. G. (2004). *Reverse Auction Bidding: An analysis of a case study*. Unpublished Professional Paper, Texas A&M University, College Station.

Weinberg, G. H., & Schumaker, J. A. (1964). *Statistics an intuitive approach*. Belmont, CA: Wadsworth Publishing Company.

Wellington, V. (personal communication to J.M.Nichols, 2006). *SQL database development for Reverse Auction Bidding site at Texas A&M University*.

VITA

Name:	Dhaval Chandresh Guhya
Address:	19 Dilkhush 44/4 Bamanpuri road JB Nagar Andheri(east) Mumbai 400059, Maharastra, India
Email Address:	dhaval.guhya@gmail.com
Education:	B.E., Civil Engineering, University of Mumbai, 2008 M.S., Construction Management, Texas A&M University, 2010